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Doctoral Thesis

A NOVEL SCHEME FOR OPERATION OF ENERGY STORAGE AND WIND GENERATION SYSTEMS CONSIDERING SECURITY COSTS

안전도 비용을 고려한 에너지 저장장치 및 풍력발전 시스템 운영구조에 대한 연구

August 2013

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ABSTRACT

Recently, the increases of both fossil fuel prices and environmental concerns have led to a boost in the installed capacity of wind power all over the world. In this trend, wind power and other renewable energies are encouraged and supported by many regulatory policies, such as the renewable portfolio standard in the United States, the renewable obligation in United Kingdom, and the feed-in tariff in the Nordic countries. However, things have changed since the deregulation took place in the electric power industry. The supporting policies tend to be redesigned with the intention of pushing renewable energies into market forces. One of the new policies is that besides receiving a general subsidy, Wind Power Producers (WPPs) need to compete for their generation, at the same time, being responsible for the problems, if any, they cause in the power system. The matter of fact is that the dependence on natural resources (*i.e.* wind energy) makes the prediction of wind power at a high degree of uncertainties; even with modern prediction tools, the error is as high as 10% – 15%, compared to the load forecasting is normally about 1% – 2% of errors. In addition, the intermittence of resources (*i.e.* wind speed) and other relative factors (*e.g.* humidity, air density, *etc.*) make the output of wind generation unreliable and fluctuating continuously. These issues remarkably decrease the competitiveness of WPPs in comparison with the conventional sources such as nuclear, coal-fired, gas-fired and hydro power plants.

In order to improve the value of wind power under market environments, many study efforts have been spent; most of them focus on the case of electricity markets in Scandinavia Peninsula, including Denmark, Sweden, Finland, and Norway (*i.e.* Nordpool). This area is famous with a high share of wind power in the power system, *e.g.* the wind power contributes about 20% of the total domestic energy consumption in Denmark in 2011, and this is thought of as the future power system in many countries. In Nordpool,

the regulation cost (also, called imbalance penalty) faced by WPPs is determined as product of the power imbalance and the regulation price; in which, the power imbalance refers to the deviation from the contracted amount ahead of time. Reviewing the state-of-the-art study in literature, we found two major approaches for improving the value of wind power: (1) a market approach and (2) a system approach.

Our study lies in the second approach which proposes the use of battery energy storage combining with wind power for providing the whole system, hereafter, called Battery/Wind Generation System (BWGS), with controllability. Then, the main contribution of the dissertation is four-fold: First, we develop a new modeling for capturing both the electrical and economic properties of batteries with sufficient details but, simple to be taken into optimization problems. Secondly, we provide a framework for the economic operation of independent Battery Energy Storage Systems (BESS) in real-time markets. The objective function is to maximize the total profit in a day which includes both the revenue in real-time markets and the battery cost. The problem is formulated using deterministic Dynamic Programming (DP) framework and solved by DP backward algorithm.

Then, we provide a framework for the economic operation of combined BWGS in real-time markets. With respect to the uncertainty of wind power, the objective is to maximize the expected profit over a day, which, also, consists of market revenues and battery costs. The problem is formulated in stochastic DP framework and solved by DP backward algorithm. Lastly, considering markets for frequency control, we propose a new battery charging/discharging scheme for wind power in response to the frequency control price. The problem is trade-off between the payment in frequency control markets and the battery cost through the optimal variation band, *i.e.* the band of output deviations. The optimality condition is derived analytically, which shows the relationship between the optimal variation band and the market price, output deviation and the battery wear cost.

Each of the problems is tested in a case study and compared with other approaches in literature. The simulation result shows that WPPs can significantly take advantages of the availability of market prices, *i.e.* spot price, real-time price and frequency control price, as well as advanced forecasting tools which also can estimate the error of prediction. These are both opportunity and challenge to all the system-users under market environments.

KEYWORDS:

Wind power producer, Battery modeling, Battery energy storage system, Deregulation, Real-time market, Frequency control market, Dynamic programming

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CHAPTER I

INTRODUCTION

For the last two decades, the electric power industry has been undergoing a major restructuring process by introducing competition in both generation and consumption sectors with the target of achieving better energy services at lower prices for the end-users. The key to this deregulation is implementing market environments where all the system-users need to compete for providing and/or consuming services, at the same time, being responsible for any side-effects they create in the system. The cause and effect of system-users are defined differently depending on market models; but in general, it is closely related to the frequency control, regulation dispatching and ahead of time scheduling in the power system. For instance, in Nordpool (*i.e.* the power pool in Nordic countries), the deviation of loads is treated in balancing markets as imbalance penalties, while in some market models in the U.S. that is reflected through the real-time pricing scheme[1], [2].

In this regard, Renewable Energy Sources (RESs) may face many difficulties in comparison with the conventional sources, such as coal-fired, gas-fired or hydro power plants. This is mainly due to the fact that the generation of RESs is uncertain as it is dependent on the natural resources (*e.g.* wind, solar, *etc.*) and many other factors such as temperature, cloud, humanity, *etc*. As a result, the prediction of RESs suffers from a large error; even with modern techniques, the error of wind prediction is as large as 10% – 15%, while that of load forecasting is only about 1% – 2% [2]. In addition, the power output of RESs is unreliable and varying as the change of inputs. These issues can remarkably affect the operation of power systems in the following aspects [3]-[7]:

- The large error in RES predictions makes the day-ahead scheduling (*i.e.* decision in the spot market) of power systems at a higher uncertainty.

Consequently, more reserve capacities are needed for a greater imbalance probably occurred in the real-time operation.

- The variation of power outputs can cause real-time imbalances in the system that requires more regulation to be dispatched (with the time basis of 5 – 10 minutes).
- The variation of power outputs also forces the system frequency deviated from the nominal value (*i.e.* 60Hz), thus, more Automatic Generation Control (AGC) are needed to keep the frequency within an acceptable limit (with the time basis of 30 seconds to 1 minute).
- And, of course, many quality problems may occur because of RESs, such as voltage sags, voltage flickers, *etc.* Thus, regulation devices such as Static Var Compensator (SVC) and/or Static Compensator (STATCOM), *etc.* are needed (instantaneous regulation).

Under market environments, these issues are accounted by many regulation services that RESs must pay to qualify themselves in power systems. Thus, the competitiveness of RESs is much reduced when compared with the conventional sources. Considering this problem, particularly the situation of wind power, a number of studies has been performed, which, in some sense, can be categorized into two approaches: (1) a market approach and (2) a system approach using Battery Energy Storage (BES).

In the market approach, some studies introduced an intra-day market (or after-sale market) with a smaller gate closure lead-time (*i.e.* the time between contracting in the spot market and the physical delivery) [3], [4]. This idea provides Wind Power Producers (WPPs) with chance to correct the contracting error in the spot market. In intra-day markets, WPPs with better estimation of their generation can submit new bids, declaring the energy service they need for the error in the spot market and the willing price; by thus the final charge for the contracting error can be reduced. Other papers proposed a bidding strategy for WPPs in spot markets to minimize the imbalance cost; the algorithm aims to take benefits on the asymmetry of the regulation price (up and down) and the availability of the probabilistic errors of the prediction tools [5]-[8]. It is recommended that WPPs should contract with a smaller amount than the mean of predictions to avoid the high cost paid for the up regulation. This approach, however, faces a major difficulty that credible models for (hour-average power) forecasting errors are not always available that requires such a long time data.

The system approach, in contrast, intends to change the system configuration by adding Battery Energy Storage (BES) (*e.g.* lead-acid battery bank) to wind power plants. The idea is to provide WPPs with controllability so that the overall power output can be adjusted appropriately with respect to the capacity of BES. As a result, if BES is properly sized and operated, not only the regulation charge can be reduced (or even eliminated) but WPPs can take the arbitrage opportunity from the market. In [10] and [11], a framework for determining the optimal short-term (daily) operation of an integrated thermal and battery/Photovoltaic (PV) system is presented. The problem is handled by dividing into two sub-problems: the well-known Lagrangian Relaxation (LR) is employed for solving the unit commitment of thermal units, while the scheduling of battery/PV is solved by Dynamic Programming (DP) method. The algorithm runs iteratively until no change in the system lambda (*i.e.* marginal cost) can be obtained. Additionally, the impacts of battery/PV on the line congestion mitigation, peak load shaving, and local marginal price are also examined [11].

In [12] and [13], the scheduling and operation of combined Battery/Wind Generation Systems (BWGSs) is formulated assuming a certain market model. The interaction of BESs with the rest of the system is only through the market price, this is different from [10] and [11], where the scheduling of battery/PV is considered as a part of the Security-Constraint Unit Commitment (SCUC) problem. In [12], an operation scheme for BWGSs is presented which consists of two modules: one is to determine the optimal scheduling ahead of time (off-line) while the other one is to operate the system in real-time based on the up-dated information (on-line). In [13], a formulation for calculating the optimal dispatch of BWGSs considering the short-term power exchange and the expected imbalance penalty in the balancing market is presented. A comparison to the case where wind and battery systems operate separately is performed. It is shown that the proposed algorithm (*i.e.* combined wind and battery) can increase the market revenue significantly, particularly in the case with high spreads of the imbalance price. Several other researches aim to develop a computational algorithm for the battery scheduling such as Multi-pass Iteration Particle Swarm Optimization (MIPSO) in [15], and fuzzy-optimization in [16].

Despite the above studies demonstrate many advantages carried by combining wind power and/or PV with batteries; they all suffer from several deficits as follows:

- The cost of using batteries is completely excluded; only the arbitrage provided by BESs in the market operation is analyzed. Thus, in some cases, the returned benefit (*i.e.* market revenue) may not be sufficient to cover the battery cost. In addition, this ignorance may lead batteries working under detrimental conditions which extremely reduce the lifetime of batteries.
- Only few researches attempted to address the contracting error (in the spot market) but it is not treated properly in the optimization algorithm, instead, a part of BESs is used as energy buffers for absorbing the real-time deviation of RESs. This, of course, leads to a sub-optimal solution.
- None of the studies addresses the real-time variation of RESs in coordination with the regulation dispatching scheme of power systems. In this regard, the deviation does not always cause power imbalance but can help to reduce it in the overall system. This possibility depends on both the generation of RESs and the actual (up or down regulation) need in the system.

- None of the above studies considers the influence of RESs on the system frequency which would be a very important issue in deregulated market environments. With this, WPPs need to pay an additional cost according to the band of their output.

In this dissertation, we try to address all the above deficiencies. First, we develop a new model of batteries considering the impact of operating conditions on the economic operation. The model is capable of capturing the electrical property of batteries with sufficient details while simple to be taken into the optimization algorithm. In addition, the model can evaluate the battery cost as a function of the operating condition, *e.g.* State Of Charge (SOC), current and time between full charges. Then, considering a new (theoretical) market model comprised of (1) a primary electricity market and (2) a frequency control market, we provide a framework for the economic operation in three different cases: (1) independent Battery Energy Storage Systems (BESSs) in real-time markets; (2) combined Battery/Wind Generation Systems (BWGSs) in real-time markets; and (3) a battery charging/discharging scheme for wind power in frequency control markets.

First, in the case of independent BESSs, the problem is to maximize the profit in real-time markets over a day. The optimization is mainly based on the market price (*i.e.* real-time price) subjected to the constraints of SOC limits, current limits and initial and final state limits, *etc*. With this problem, deterministic DP framework and DP backward algorithm are used for solutions. The solution called "control policy" is a set of function of the system state which gives the optimal control to the system for a given system state.

In the case of combined BWGSs, the problem is also to maximize the total profit in a day. In this problem, BES needs to compensate the uncertainty of wind generation and control the overall output of BWGS. Therefore, the optimization is based on not only the market price but also the statistic information of wind generation. With uncertainties, the stochastic DP framework is used for solutions. The control policy achieved by DP backward algorithm is a set of functions of the system state which gives the optimal control to the system for a given system state. Thus, the operation scheme consists of two levels of hierarchy: (1) an off-line scheduling based on predictions and (2) an on-line control following the off-line schedule and the updated information of the system.

Finally, we assume there is a market for frequency control where WPPs need to pay for their impact on the system frequency. The payment is calculated according to the band of output variations. In this problem, BES is used to regulate the variation band of wind power which minimizes the payment in frequency control markets. Considering battery costs, the more BES is used, the smaller charge is in frequency control markets, but the larger battery cost is; and vice versus. Thus, the optimization can be thought of as a tradeoff between the payment for frequency control and the battery cost. The statistics of real-time outputs and frequency control price are the two major inputs needed for this problem.

The dissertation is organized as follows. Chapter II presents a new theoretical model of deregulated electricity markets. The market consists of two qualitatively different sub-markets: (1) a primary electricity market (including day-ahead markets and real-time markets) and (2) a frequency control market. The principle of market participants, trading scheme and settlements in different sub-markets is discussed. This market model will serve as a platform in this dissertation.

Chapter III surveys some forecasting techniques for wind power; some techniques are simple such as persistence model and aggressive model while others are very complicated, *e.g.* Numerical Weather Prediction (NWP). All of them have advantages and disadvantages; for example, the persistence model takes advantages of computation and suitable for short-term predictions (smaller than 3 hours), while NWP is usually run on super computers but satisfactory for long-term predictions (larger than 6 hours).

Chapter IV reviews some power system applications of DP method. The DP method is widely used and very effective for treating the uncertainty and inter-correlated problems such as unit commitment, energy storage scheduling, demand response, *etc.* The formulation in this dissertation again proves the huge potential of DP in the field of electrical engineering.

Chapter V presents the mathematical formulation of batteries for economic operations; this consists of both modeling for the electrical and economic properties of batteries. Based on Ah-throughput model, the impact of operating conditions on the battery lifetime is formulated and the battery cost is modeled as a function of operating conditions, considering three important factors: SOC, current and time between full charges, *etc.*

Chapter VI provides a framework for the economic operation of independent BESSs in real-time markets. The problem is formulated using deterministic DP framework and solved by DP backward algorithm. The test in a case study is performed with the intention of examining the economic operation, the validity of battery models and analyzing the sensitivity with respect to the battery cost.

Chapter VII provides a framework for the economic operation of combined BWGSs in real-time markets. With the uncertainty of wind power, the problem is formulated using stochastic DP framework and solved by DP backward algorithm. The problem is then tested in a case study to demonstrate the economic operation of combined WBGSs, as well as show the effectiveness of combining battery and wind power when compared with the case they operate separately.

Chapter VIII presents another battery approach for wind power considering frequency control markets. The problem is trade-off between the BES cost and the payment for frequency control. The optimality condition is derived analytically in this problem, showing the relationship between the optimal variation band, market price and the stochastic variation of power outputs. Again, the problem is applied in a case study where the comparison with other operation strategies for frequency control is performed.

Chapter IX summarizes the key findings of this study and recommends its possible extension in future work.

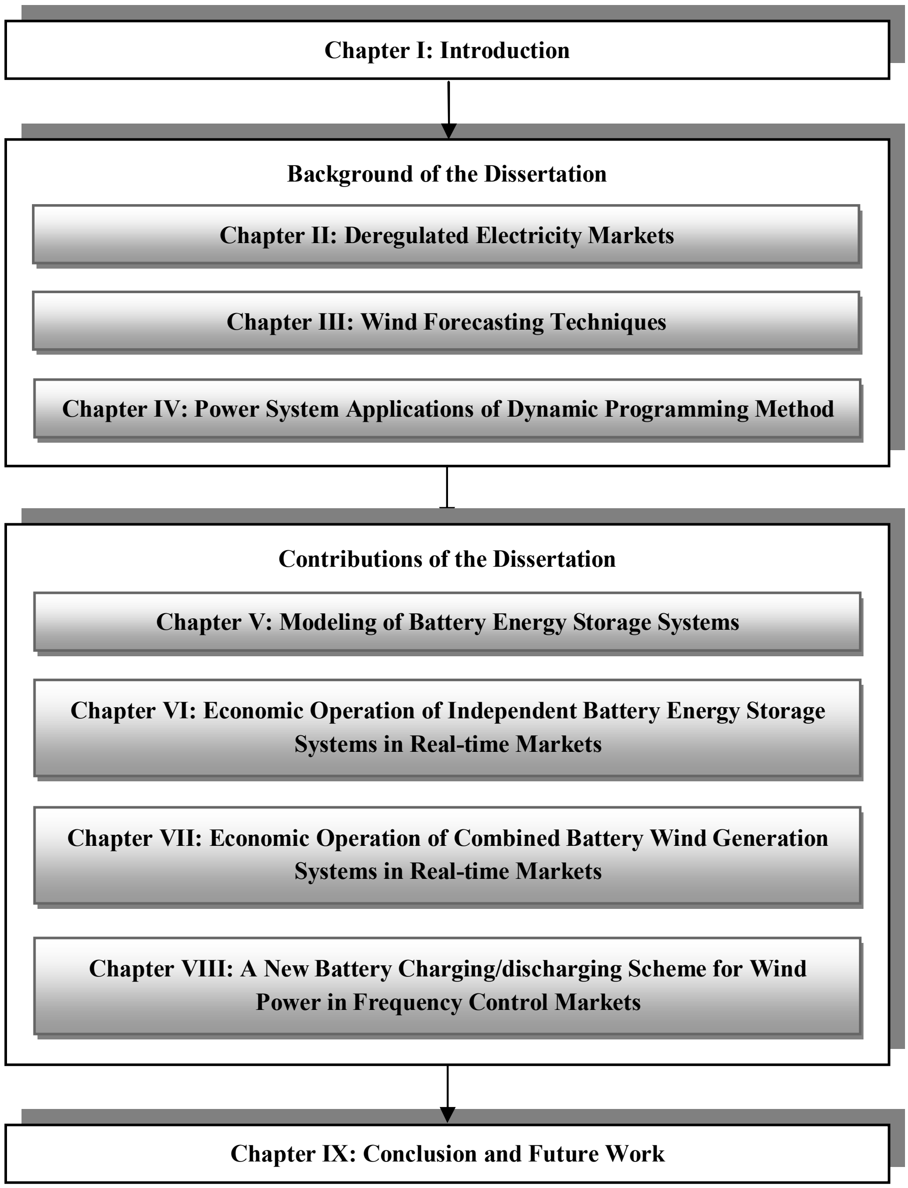

FIGURE 1.1 DISSERTATION ORGANIZATIONS

CHAPTER II

DEREGULATED ELECTRICITY MARKET

2.1 PRINCIPLE OF BALANCING IN POWER SYSTEMS

Power balancing in the electric power system is guaranteed by two distinct processes: (1) an open-loop scheduling for anticipated demands, and (2) an automated regulation for the real-time imbalance caused by the deviation of loads and (rarely) generators from the advanced schedule. This automated regulation may refer to Automatic Generation Control (AGC) and only provided by a handful of technically qualified generators in power systems. Mathematically, the static performance of a conventional generating unit formed of Governor-Turbine-Generator (G-T-G) can be expressed as follows, [20]:

$$\omega_{Gi} = \left(1 - \sigma_{Gi} d_{Gi}\right) \omega_{Gi}^{ref} - \sigma_{Gi} P_{Gi} \tag{2.1}$$

where

ω_{Gi} is the rotating velocity of generating unit Gi, [rad/s]

P_{Gi} is the power output of generating unit Gi, [MW]

d_{Gi} is the damping coefficient of generating unit Gi, [MW/rad/s]

ω_{Gi}^{ref} is the reference velocity of generating unit Gi, [rad/s]

$\sigma_{Gi} = {-\partial\omega}/{\partial P_{Gi}}$ is the droop defining the sensitivity of system frequency ${\omega}/{2\pi}$ with respect to the change of power generated by generating unit Gi, [rad/s/MW]

Equation (2.1) represents the relationship of the instantaneous power output and the system frequency, *i.e.* static model of G-T-G units. If the unit does not participate in AGC, ω_{Gi}^{ref} is kept constant during operations; otherwise it is used to control the power output with a participation factor. Equation (2.1) can be rewritten in order to distinguish the amount produced by this direct control and the other caused by the system frequency deviation:

$$P_{Gi}(\omega) = P_{Gi}^{c} - \beta_{Gi}\omega \tag{2.2}$$

$$P_{Gi}^{c} = \frac{\left(1 - \sigma_{Gi} d_{Gi}\right)\omega_{Gi}^{ref}}{\sigma_{Gi}} \tag{2.3}$$

$$\beta_{Gi} = \frac{1}{\sigma_{Gi}} \tag{2.4}$$

where

P_{Gi}^{c} is the amount generated by direct controls (*i.e.* adjusting ω_{Gi}^{ref}), [MW]

β_{Gi} is the droop defining the sensitivity of the power output of unit Gi to the system frequency, [MW/rad/s]; Thus, the last term in (2.2) represents the response of unit Gi to the deviation of the system frequency.

It is worth noting that the above variables denote the deviation from their nominal values; for example, ω is the frequency deviation from its nominal value, *i.e.* 2π·60 [rad/s].

An aggregate load also responds to the change of the system frequency; similarly, its instantaneous consumption can be decomposed into two parts: a frequency-independent and -dependent part, as follows.

$$P_{Lj}\left(\omega\right)=P_{Lj}^{c}+\beta_{Lj}\omega \tag{2.5}$$

where

P_{Lj}^{c} is the part independent from the system frequency, [MW]

β_{Lj} is the droop defining the sensitivity of loads to the system frequency, [MW/rad/s]

Equations (2.2) and (2.5) represent the well-known self-stabilizing characteristics of power systems. That is, generators and loads automatically adjust the output themselves in response to the change of the system frequency and in the way that balances the overall system. The relationship of system imbalances and frequency deviations can be expressed as follows.

$$\begin{aligned} P_{imb} &= \sum\nolimits_{i=1}^{N} P_{Gi}^{c} - \sum\nolimits_{j=1}^{L} P_{Lj}^{c} \\ &= \omega\left(\beta_G + \beta_L\right) \end{aligned} \tag{2.6}$$

where

N is the set of generators within the power system

L is the set of aggregate loads within the power system

$\beta_G = \sum\nolimits_{i=1}^{N} \beta_{Gi}$ is the sum of droop parameters of all generators in the power system, [MW/rad/s]

$\beta_L = \sum\nolimits_{j=1}^{L} \beta_{Lj}$ is the sum of droop parameters of all loads in the power system, [MW/rad/s]

The AGC set-up on fast-response generators (*e.g.* gas-fired power plants) can be designed as follows.

$$P_{Gi}^{agc}\left[kTs\right]=G_{Gi}\omega\left[kTs\right] \tag{2.7}$$

where

G_{Gi} is the AGC participation factor of generator Gi, [MW/rad/s]

Ts is the time constant of AGC activation (*e.g.* 30 second or 1 minute)

k is the time index of AGC activation

Recall (2.2), indeed, the AGC generation is a part of the controllable amount (P_{Gi}^{c}) of G-T-G units and is controlled through the reference, ω^{ref}. The time-discrete formula in (2.7) is to capture the fact that AGC is activated discretely, usually with a time constant of 30 seconds or 1 minute. The necessary condition for the AGC scheme to recover the system frequency (*i.e.* fully compensate for the system imbalance) is:

$$\sum\nolimits_{i=1}^{N}G_{Gi}=\beta_G+\beta_L \tag{2.8}$$

It is noted that the above formulation (2.1 – 2.8) is valid only for single control area systems. In case of multi-interconnected area systems, the formulation can be a bit modified by taking into account the deviation of power transferring between areas, *i.e.* tie-line power flows. This issue will be discussed in details later.

The task of maintaining the system frequency within an acceptable limit is belonging to System Operator (SO) and the relevant cost is passed to customers bundled in the electricity price. Under market environments, it is important to relate the cause and effect of system-users, meaning their right and responsibility needs to be cleared. In this regard, the regulation needs to be unbundled from the energy service and being settled separately. This leads to the deregulation of electricity markets into several sub-markets for different services, *e.g.* energy services, regulation services and/or frequency control services. In this study, we consider a new model of electricity markets which consists of (1) a primary electricity market and (2) a frequency control market.

2.2 MARKETS FOR ENERGY SERVICES

These markets are for trading energy services, *i.e.* electricity in term of megawatt-hour (MWh). Based on the time and manner that the market decision is made, as well as the market price is determined and posted, markets for energy services are sub-divided into: a day-ahead (spot) market and a real-time market.

2.2.1 DAY-AHEAD (SPOT) MARKET

Day-ahead (spot) markets are usually managed by Market Operator (MO) and scheduled for the anticipated demand in the next day, *i.e.* day-ahead. In this market, producers and consumers can submit bids clarifying the quantity and corresponding price of electricity they are willing to sell or purchase; MO collects the bids, constructs the selling and purchasing curve and decides which bids to be accepted for each hour of the next day. Then, the Market Clearing Price (MCP) is determined as the intersection of the selling and purchasing curve; this is equivalent to the highest price of the accepted selling bids or lowest price of the accepted purchasing bids [Figure 2.1].

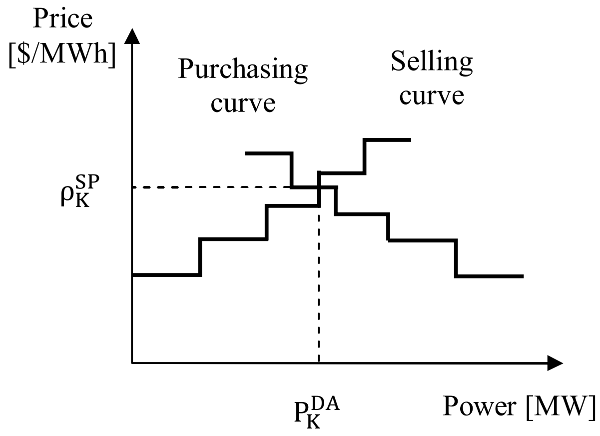

FIGURE 2.1 PRINCIPLE OPERATION OF DAY-AHEAD SPOT MARKETS

where

ρ_K^{SP} is the market clearing price (*i.e.* spot price) at K-th stage of day-ahead markets, [$/MWh]

P_K^{DA} is the sum of accepted bids at K-th stage of day-ahead markets, [MW]

Day-ahead markets are usually closed at noon and twelve hours before the physical delivery of electricity (*i.e.* 12 – 36 h ahead). The bidding strategy of WPPs in this market is studied exclusively in [5]-[9], this is out of the scope of this dissertation.

2.2.2 REAL-TIME MARKET

Real-time markets are managed by Independent System Operator (ISO) to deal with the real-time imbalance caused by loads' variations (and non-conventional sources) in power systems. In real-time markets, technically qualified (fast-response) generators can submit bids for fast increase and/or decrease of their power output. The bids are then arranged in price order (from the cheapest to the most expensive), by thus, based on the actual need (*i.e.* power imbalance) of the system, ISO decides which bid (*i.e.* up/down regulation) to be selected. The highest or lowest price of the up/down bid being used gives the regulation price [Figure 2.2].

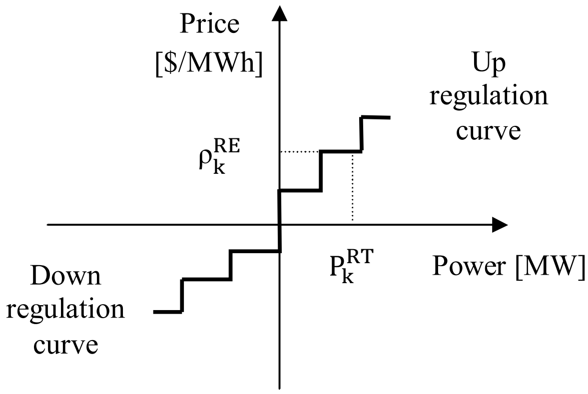

FIGURE 2.2 PRINCIPLE OPERATION OF REAL-TIME MARKETS

where

ρ_k^{RE} is the regulation price at k-th period of real-time markets, [$/MWh]

P_k^{RT} is the actual need in the system, [MW]

Up to this point, the real-time market presented here is similar to what described in Nordpool, called balancing markets. The difference lies on the time basis when the market decision is made. In [6], the regulation price is set uniquely in the time basis of the spot market (hourly), which is equivalent to the most expensive upward or cheapest downward regulation of the selected bids. In this study, we consider the model of real-time markets that the price is set in accordance to when and how much the regulation is actually needed in the system with the time basis of 5 minutes. The real-time price is posted in the end of each stage of the day-ahead spot market (*i.e.* hourly), thus called *ex-post* price. The real-time price is determined based on the spot price and the regulation price, as follows.

$$\rho_k^{RT} = \rho_K^{SP} + \rho_k^{RE} \tag{2.9}$$

where

ρ_k^{RT} is the real-time price, [$/MWh]

2.3 MARKETS FOR FREQUENCY CONTROL

2.3.1 HIERARCHICAL CONTROL SCHEME

It is impossible to keep the system frequency always at desire (60Hz); the matter of fact is that the power imbalance caused by system-users continuously forces the system operating with a frequency deviation [16]. For this reason, the well-known hierarchical control scheme has long been used for maintaining the system frequency within an acceptable limit; this consists of a primary, a secondary and a tertiary regulation level [20]-[22].

The primary regulation level refers to the power adjusted spontaneously by G-T-G units when the system frequency deviates from the reference as expressed in (2.2) – (2.6); this is called droop-control or governor-free. This action is fast and usually stabilizing the system within 5 – 10 seconds. In power systems, loads also respond to the change of frequency, however, this action is associated with high uncertainties; thus, in general, loads are not considered as sources of primary regulations [17]. It is worth noting that this level of regulation does not fully compensate for the power imbalance, but stabilizes the power system at a new equilibrium point with a small deviation of the frequency.

The secondary regulation level refers to the generation controlled by AGC set up on the technically qualified generating units, *e.g.* gas-fired generators [17]. This action is activated with a time constant of minutes, aiming to restore the system frequency to its nominal value. It is worth noting that this regulation level is only to compensate for the normal (slow and small) variation of loads (and nonconventional sources as well); thus, it is also called load-following. In multi-area systems, AGC is based on the Area Control Error (ACE) signal. Fundamentally, ACE reflects the power imbalance within each control area [20]-[23]:

$$ACE_i = \left(\beta_G + \beta_L\right)_i \omega + \sum\nolimits_{j=1}^{J} F_{ij} \tag{2.10}$$

where

- ACE_i is ACE signal for i-th area, [MW]
- F_{ij} is the deviation from the schedule of power transferring between i-th and j-th area, [MW]
- J is the set of areas connected to i-th area through tie-lines
- $(\beta_G + \beta_L)_i$ is the sum of droop parameters of all generators and loads within i-th area, [MW/rad/s]

Then, AGC generation of unit Gi in i-th area according to the participation factor is determined as follows.

$$P_{Gi}^{agc} = G_{Gi} \cdot ACE_i \tag{2.11}$$

The participation factor of all AGC generators within a control area subjects to a constraint that sum of them must be equal to one.

The tertiary regulation level refers to the generation being called in case when a large power imbalance occurs in power systems, *e.g.* caused by the unexpected change of loads or loss of important transmission lines or generators. These disturbances can cause the system out of limits, *i.e.* frequency limits, voltage limits, and/or transmission line capacity limits, *etc.* In this case, rescheduling of generators and transmission lines in system-wide is required. This action typically takes more than 10 minutes, and therefore, permits the wide participation of demand-side (*i.e.* load-shedding), spinning and non-spinning generators [17].

2.3.2 TRADING OF FREQUENCY CONTROL

In monopoly industry, the task of maintaining the system frequency with the limits belongs to System Operator (SO) and the cost is passed to consumers bundled in the electricity price. Under market environments, however, the cause and effect of system-users should be clear. For this reason, markets for frequency control have been proposed defining the right and responsibility of each system-user to the system frequency, *i.e.* loads (and non-conventional sources) need to pay and AGC generators get paid for the frequency regulation they consume or produce in power systems [20]. The price of frequency control is defined in term of payment per capacity reversed for AGC in generators, [$/MW], and payment per variation band of loads (and non-conventional sources), [$/MW].

Frequency control services can be traded either through a power pool or bilateral contracts [17], [18]. The power pool for frequency control in a specific area is managed by ISO through a bidding mechanism. Bilateral contract, in difference, can be dealt between individual providers and consumers both within and across the boundary of control areas. In this case, ACE signal, *i.e.* the amount trading in pools, can be calculated as follows, [21] and [22].

$$ACE_i = \left(\beta_G + \beta_L\right)_i \omega + \sum\nolimits_{j=1}^{J} F_{ij} - \sum\nolimits_{l=1}^{Bi} \Delta Pb_l \tag{2.12}$$

where

Bi is the set of consumers within i-th area who have bilateral contract for frequency control

ΔPb_l is the power deviation of consumer l∈Bi, [MW]

AGC set on generator Gi according to the participation factor is:

$$P_{Gi}^{agc} = G_{Gi} \cdot ACE_i + \sum_{l=1}^{Bi} \Delta Pb_{il} \tag{2.13}$$

where

G_{Gi} is the participation factor of generator Gi in the pool for frequency control, [MW/Hz]

ΔPb_{il} is the power deviation of consumer l who has bilateral contracts for frequency control with generator Gi, [MW]

B_{Gi} is the set of customers who have bilateral contracts with generator Gi

The payment for frequency control (of loads and nonconventional sources) is calculated based on the variation band and market price (*i.e.* frequency control price) as:

$$C_k^{\mathrm{FC}} = \Delta P_k^{\pm} \cdot \rho_k^{\mathrm{FC}} \tag{2.14}$$

where

k is the time index of the market for frequency control (*e.g.* hourly)

C^{FC} is the cost of frequency control, [$]

$\Delta P^{\pm}$ is the variation band, [MW]

ρ^{FC} is the price of frequency control, [$/MW]

2.4 MARKET SETTLEMENTS

The settlement in day-ahead markets is straightforward based on the accepted bid and the market clearing price (*i.e.* spot price) as follows.

$$[\text{Payment}]_K = \rho_K^{SP}\left[\$/MWh\right]\cdot P_K^{DA}\left[MWh\right] \tag{2.15}$$

In real-time markets, the provider of regulations gets paid according to the real-time price (*ex*-post) and the increment and/or decrement of their output. However, the payment scheme for consumers is a bit different depending on both their consumption and the situation of the overall system. That is, the deviation of loads does not always cause imbalances in power systems but can help to reduce them. Then, in case loads help to balance the system, *i.e.* the deviation is positive when down regulations are ordered (*i.e.* excess of power) and vice versus, these loads are not considered of consuming regulations, therefore, they pay or get paid according to the spot price. Only loads with deviations that contribute to the imbalance of the overall system are considered of consuming regulations, their deviation needs to be charged according to the real-time price. The payment scheme in this market can be expressed mathematically as follows.

$$\left[\text{Payment}\right]_k = \begin{cases} \rho_k^{RT}\left[\$/MWh\right]\cdot\Delta P_k\left[MWh\right] & \begin{pmatrix}\text{if the deviation contributes}\\ \text{to the system imbalance}\end{pmatrix} \\ \rho_k^{SP}\left[\$/MWh\right]\cdot\Delta P_k\left[MWh\right] & \begin{pmatrix}\text{if the deviation helps to}\\ \text{reduce the system imbalance}\end{pmatrix}\end{cases} \tag{2.16}$$

In markets for frequency control, the payment scheme is also clear as production of the market price and the quantity of services:

$$\left[\text{Payment}\right]_K = \rho_K^{FC}\left[\$/MW\right]\cdot\Delta P_K^{\pm}\left[MW\right] \tag{2.17}$$

The closure lead-time and settlements in different markets are displayed in Figure 2.3.

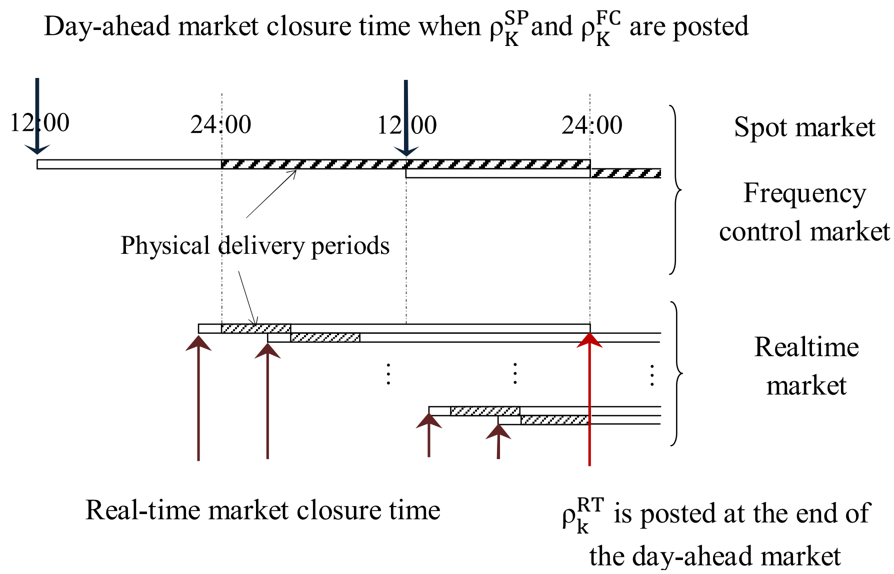

FIGURE 2.3 MARKET CLOSURE LEAD-TIME, ACTUAL DELIVERY AND PRICE-POSTING TIME

CHAPTER III

WIND FORECASTING TECHNIQUES

The increasing penetration of wind power in power systems has led to a need of tools for more reliable and accurate prediction. There are two approaches widely used for wind power prediction: physical models and statistical models [24]. The first approach includes physical consideration for the best prediction precision, hence, takes advantage of long-term prediction; while the second one mainly based on relationships of the on-line measured power data, is suitable for short-term prediction. Recently, some new methods based on artificial intelligence are catching scientific attention, such as Artificial Neural Network (ANN) and fuzzy logic models [25]. In this study, we classify these forecasting techniques into four categories: (1) physical models, (2) conventional statistical models, (3) spatial correlation models, and (4) the artificial intelligence models, [24], [25].

3.1 PHYSICAL MODEL

Physically, the power generated by a wind-turbine-generator unit mainly depends on wind speed, thus in some sense, the forecasting of wind generation and wind speed has the same principle. In physical models, the physical and metrology information are used to estimate the wind speed in future; sometimes, this is only the first step of forecasting the wind generation, which is supplied as auxiliary inputs of the statistic model. The state of the atmosphere can be described by seven meteorological variables: pressure, temperature, amount of moisture, air density and wind velocity. The behavior of these variables is governed by seven physical equations, three arising from thermodynamic and four arising from hydrodynamic performances of the atmosphere [24]. These seven governing equations involve the state variables and their spatial and time derivatives. Numerical

Weather Prediction (NWP) is an objective forecast in which the future state of the atmosphere is determined by the numerical solution of a set of equations describing the evolution of meteorological variables (*i.e.* atmosphere model). Even there is huge progress in the last two decades with approximately doubling of forecast skills, NWP still need more improvements regarding to: (1) better atmosphere models, (2) better observational data and (3) better methods for data assimilation. NWP models can be the global or limited area models. The limited area model is nested within the global model.

The High-Resolution Limited Area Model (HIRLAM) is widely used in Europe and is a result of cooperation between the meteorological institute of Denmark, Finland, Iceland, Ireland, Netherlands, Norway, Spain, Sweden and France; this receives the lateral boundary condition from the European Center for Medium Range Weather Forecasting (ECMWF), *i.e.* global atmospheric model, every six hours. As NWP are large-scale forecasting, when looking at the specific location of wind turbines, technical tools should be used for taking the effect of obstacles, roughness, *etc.* into account, at the same time, considering the shading effect of turbines to each other as well. WAsP, PARK and MOS (Model Output Statistic) are the techniques widely used for these purposes.

Since NWP models are complex mathematical models, they are usually run on super computer; this limits the method from the on-line or short-term application in power systems. However, with a high degree of accuracies, NWP models are satisfactory for long-time (larger than 6 hours ahead) horizon and not for short-term predictions (several minutes to one hour).

3.2 CONVENTIONAL STATISTIC MODEL

Conventional statistic models are identical to direct random time-series models. Based on a number of historical data, pattern identification and parameter estimation, the model checking are utilized to make a mathematical model for the prediction. The conventional statistic model includes: Autoregressive (AR) model, Moving Average (MA), Autoregressive Moving Average (ARMA) model and Autoregressive Integrated Moving Average (ARIMA) model. The random time-series can be described as follows.

$$x_t = \sum_{i=1}^{n} \varphi_i x_{t-i} + \alpha_t - \sum_{j=1}^{m} \theta_j \alpha_{t-j} \tag{3.1}$$

where

φ_i	is the autoregressive parameter
θ_j	is the moving average parameter
α_t	is the normal while noise
x_t	is the value of wind speed at time t, [m/s]

Equation (3.1) represents a typical ARMA model, if θ_j is set to be zero, it becomes AR model, likewise, if φ_i is zero, it will be MA model.

Persistence model is the simplest and most widely used statistic model for wind forecasting. The model is based on an assumption that the wind power will be the same as the last measurement. This model can be expressed mathematically as follows.

$$p_{t+k} = p_t + \alpha_{t+k}$$

or

$$\hat{p}_{t+k} = p_t \tag{3.2}$$

where

p_t, p_{t+k}	is the power at time t and t+k, respectively
$\hat{p}_{t+k}$	is the expected value (forecasting) of power at time t+k with the measurement at time t

The model is very simple but powerful in short-term prediction (0 to 3 hours) due to the fact that the changes in the atmosphere take place rather slowly. Therefore, persistence model is usually used as a reference model against more advanced methods.

Recently, a new reference model has been proposed which is as weighting between the persistence and the mean value [26]. Mathematical expression is:

$$\hat{p}_{t+k} = a_k p_t + \left(1 - a_k\right) \overline{p} \tag{3.3}$$

$$\overline{p} = \frac{1}{N} \sum_{t=1}^{N} p_t \tag{3.4}$$

$$a_k = \frac{\frac{1}{N} \sum_{t=1}^{N-k} \tilde{p}_t \tilde{p}_{t+k}}{\frac{1}{N} \sum_{t=1}^{N-k} \tilde{p}_t^2} \tag{3.5}$$

$$\tilde{p}_t = p_t - \overline{p} \tag{3.6}$$

where

$\overline{p}$ is the mean power of estimation

a_k is the correlation coefficient between p_t and p_{t-k}

When k is small (short-term forecast), a_k would approach one and equation (2.13) becomes persistence models. But when k is large (long-term forecast), a_k would be zero and the estimate is simply the mean value.

Another statistic model is Kalman filter. The model considers wind speed as a state variable of the state-space model and Kalman filter algorithm is used to estimate the state variable in real-time. Thus, this method is suitable for online applications of wind forecasting.

3.3 SPATIAL CORRECTION MODEL

Different from previous models, spatial correlation models take the spatial relationship of different sites' wind speed into account. The time-series of the wind speed in predicted points and its neighboring sites are employed to predict the future wind speed. This kind of model is a bit more difficult in practice since the measurement of wind speed in many spatially correlated sites is needed. Some studies compared the spatial correlation model with the data from remote sites and the conventional statistic model (*e.g.* persistence model) regarding to the sites' terrain, *e.g.* flat terrain, and rough and complex terrain. The result shows that the neighborhood data can improve the accuracy in the flat terrain while in the complex terrain, it is even worse. Other studies analyze the effect of the number of neighborhood sites on the error reduction of spatial correlation modes. It is shown that only a few sites are sufficient for the error reduction to get its saturation level.

3.4 ARTIFICIAL INTELLIGENCE MODEL

Recently, with the emergence of artificial intelligence, a number of new forecasting techniques have been proposed such as ANN, fuzzy logic method, support vector machine and some hybrid models. ANN is one of the most widely used models in the last decade, this model consists of many layers, an input layer, an output layer and one or more hidden layers. There are a lot of neurons in each layer, which are connected to neurons of the previous layers while the neurons in the same layer are independent with each other. Each connection has its own weight, and each neuron has a transfer function (in the hidden layer it usually is sigmoid function). A training process is used to obtain the weights of each connection and the neurons threshold value. Some training algorithms were developed, including Back-propagation (BP) algorithm, Levenberg Marquardt (LM) algorithm and so on, with the intention of achieving the minimum of network errors.

Another model is called fuzzy logic model; it utilizes membership values in the interval [0, 1] and the fuzzy variables like long, medium and short, to explain their membership. It is used where a system is difficult to model accurately. Support vector machine is a novel approach which can overcome some disadvantages of neural network, such as local minimal point, over learning, *etc.*

The forecasting techniques presented above have their own features, advantages and disadvantages over others. For example, NWP models are good for large-scale wind farms and can achieve better results with long-term predictions. Often time, they are used as inputs of time-series models such as ARMA, ANN, *etc.* and help them to obtain better results. Persistence models are the simplest time-series models but can surpass many others in a very short-term prediction. In spite of unstable efficiency, they have been widely used in practice. Recently, combined persistence and mean models was proposed as a new reference against the advanced model.

CHAPTER IV

POWER SYSTEM APPLICATIONS OF DYNAMIC PROGRAMMING METHOD

4.1 DYNAMIC PROGRAMMING

Dynamic Programming (DP) problem is to minimize the total (expected) cost over a time horizon. The DP formulation includes control units, system states, and uncertainty quantities; mathematically, this can be expressed as follows.

$$\frac{\partial x(t)}{\partial t} = f\left(x(t), u(t), w(t)\right), \qquad 0 \le t \le T \qquad x(0)\text{: given,} \tag{4.1}$$

$$\min_{u(t)} \; \mathop{\mathrm{E}}_{w(t)} \left\{ h\left(x(T)\right) + \int_0^T g\left(x(t), u(t), w(t)\right) dt \right\} \tag{4.2}$$

where

x(t)	is the vector of state variables at time t
u(t)	is the vector of control variables at time t
w(t)	is the vector of uncertainties (*i.e.* random variables) at time t
T	is the terminal time

Equation (4.1) represents the dynamic performance of the system: f is continuously differentiable with respect to x and is continuous with respect to u. Equation (4.2) represents the total cost over [0 – T]: g and h are continuously differentiable with respect to x and g is continuous with respect to u; and $\underset{w(t)}{E}$ denotes the expected value with respect to uncertainties, w(t).

Despite (4.1) and (4.2) can model the natural (*i.e.* time-continuous) dynamic performance of many engineering systems; their solution suffer from huge a computation burden. Therefore, in practice, the time horizon is often broken into a discrete-time series (*i.e.* stages) and the system state is discretized into a finite number of states. The problem then becomes the so-called "discrete finite state" problem, as follows:

$$\begin{aligned} x_{k+1} = f_k\left(x_k, u_k, w_k\right), \qquad & k = 1,\ldots,N-1 \\ x_0\text{: given,} \qquad & \end{aligned} \tag{4.3}$$

$$\min_{\substack{u_k \\ k=0,\ldots N-1}} \underset{\substack{w_k \\ k=0,\ldots N-1}}{E} \left\{h\left(x_N\right) + \sum_{k=0}^{N-1} g_k\left(x_k, u_k, w_k\right)\right\} \tag{4.4}$$

The control u_k is restricted to a set of admissible controls $U_k(x_k)$ and is usually chosen by:

$$u_k = \mu_k\left(x_k\right) \tag{4.5}$$

The set of functions $\mu_k\left(x_k\right)$ for all k is defined as the control policy. The schematic diagram of DP problems can be displayed as in Figure 4.1.

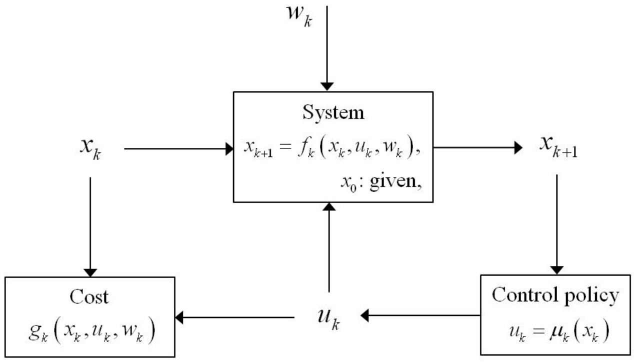

FIGURE 4.1 DYNAMIC PROGRAMMING FRAMEWORK

The discrete finite state DP formulated in (4.3) and (4.4) can be solved by the well-known DP backward algorithm to find the control policy that minimizes the total expected cost over N stages. The algorithm is as follows:

$$\begin{cases} J_N(x_N) = h_N(x_N) \\ J_k(x_k) = \min\limits_{u_k \in U_k(x_k)} \mathop{\mathrm{E}}\limits_{w_k} \left\{ g_k(x_k, u_k, w_k) + J_{k+1}\left(f_k(x_k, u_k, w_k)\right) \right\} \end{cases} \tag{4.6}$$

where

$J_k(x_k)$ is the performance index, called cost-to-go function, which denotes the optimal expected cost when starting at stage k assuming the system state is x_k

$h_N(x_N)$ is the terminal cost

The DP backward algorithm is to find the optimal policy as a set of functions, $\mu_k^*(x_k)$, which gives the optimal control, $u_k^* = \mu_k^*(x_k)$, for given system state, x_k. This algorithm, in turn, guarantees the optimality of the solution.

4.2 UNIT COMMITMENT

4.2.1 REGULATED INDUSTRY

Unit Commitment (UC) is the process of deciding whether to turn on or off each generator at a given time (hour) in power systems. Since generators cannot instantly turn on and produce electricity, UC problem must be planned in advance so that enough generation is available to handle the system demand with adequate reserve margins for the event that generators or transmission lines go out or demands exceed the expected amount. In monopoly industry, UC problem is to minimize the total expected cost over a time horizon (*e.g.* a day or a week). The cost includes generation (or fuel) costs, start-up and shut-down costs, the cost of failing to serve loads (*i.e.* insurance payments), and the revenue received for each unit of energies used by loads [38].

$$\min_{\substack{u_k \\ k=1,\ldots N}} \quad \underset{\substack{P_{Li,k} \\ k=1,\ldots N}}{\mathrm{E}} \Big\{ \sum_{k=1}^{N} \sum_{i=1}^{N_g} c_{Gi}\left(P_{Gi,k}\right) + u_{i,k} I\left(x_{i,k} < 0\right) S_i + \\ + \left(1-u_{i,k}\right) I\left(x_{i,k} > 0\right) T_i + \sum_{i=1}^{N_L} \left(1-R_{Li}\right) I_{Li,k} - \rho_i^e P_{Li,k} \Big\}, \tag{4.7}$$

where

$u_{i,k}$	is the control decision of unit i at k-th stage (1 = On, 0 = Off)
$x_{i,k}$	is the state of unit i at k-th stage
ρ_i^e	is the unit price of load i, [$/MWh]
P_{Li}	is the real power used by load i, [MW]
c_{Gi}	is the generation cost of unit i, [$]
P_{Gi}	is the power output of unit i, [MW]

S_i is the start-up cost of unit i, [$]

T_i is the shut-down cost of unit i, [$]

R_{Li} is the rationing of load i (1 = Served, 0 = Dropped)

I_{Li} is the insurance payment to load i in event of losing services, [$/MWh]

I is the indicator variable (1 = the statement is true, 0 = it is false)

In (4.7), the first term is the generation cost, the second term is the start-up and shut-down cost, and the third term is the insurance payment for load interruption. The system state, $x_{i,k}$, denotes the time that the generator has been on or off: $x_{i,k}$ is positive if the generator has been on for $x_{i,k}$ hours and negative if it has been off for $-x_{i,k}$ hours. The transition of system states can be described as follows [38].

$$x_{i,k+1} = \begin{cases} \max\left(1, x_{i,k}+1\right) & : u_{i,k}=1 \\ \min\left(-1, x_{i,k}-1\right) & : u_{i,k}=0 \end{cases} \tag{4.8}$$

The admissible control, $U_k(x_k)$, are defined based on the capability of turning on or off generators at a given time [38]:

$$\begin{cases} u_{i,k+1} \geq I\left(1 \leq x_{i,k} < t_{up}\right) \\ u_{i,k+1} \leq 1 - I\left(-t_{dn} < x_{i,k} \leq -1\right) \end{cases} \tag{4.9}$$

where

t_{up} is the minimum-up time, [hour]

t_{dn} is the minimum down time, [hour]

Both (4.8) and (4.9) imply that generators must remain on or off for a certain time (t_{up} and t_{dn}) before it can be switched (off or on). This is called minimum-up time and minimum-down time constraints.

4.2.2 UNDER MARKET ENVIRONMENTS

Under market environments, UC problem is to make ON/OFF decision of individual Independent Power Producers (IPPs). It is assumed that IPPs are capable of selling as much power as desired at the market price, ρ_k^e, the objective function becomes maximizing the total expected profit over a time horizon, *e.g.* a day [38].

$$\max_{\substack{u_k \\ k=1,\dots N}} \; \underset{\substack{\rho_k^e \\ k=1,\dots N}}{\mathrm{E}} \left\{ \sum_{k=1}^{N} \sum_{i=1}^{N_g} u_{i,k} \left(\rho_k^e P_{Gi,k} - c_{Gi}\left(P_{Gi,k}\right) - I\left(x_{i,k} < 0\right) S_i \right) - \left(1 - u_{i,k}\right) I\left(x_{i,k} > 0\right) T_i \right\}, \tag{4.10}$$

With the generation cost is modeled as a quadratic function:

$$c_G\left(P_G\right) = aP_G^2 + bP_G + c \tag{4.11}$$

The optimal generation level, P_{Gi}, can be regarded as a function of the control unit, u_k, and the market price, ρ_k^e, as follows [27]:

$$\begin{cases} P_{Gi,k} = 0 & \text{if} \quad u_{i,k} = 0 \\ P_{Gi,k} = \dfrac{E\left\{\rho_k^e\right\} - b_i}{2a_i} & \text{if} \quad u_{i,k} = 1 \end{cases} \tag{4.12}$$

4.3 HOME ENERGY MANAGEMENT SYSTEMS

Demand Response (DR) poses a big opportunity for both power providers and consumers in deregulated electricity markets, particularly under real-time pricing environments. Responding to the variation of market prices, generators can produce more electricity when the price is high to make profits, while loads can adjust their consumption (*e.g.* shedding, shifting or rescheduling) to the low price time to reduce the energy charge. In this section, we introduce one of DR programs, called Home Energy Management System (HEMS). This software-based program is to control the energy consumption within a household for minimizing the electricity charge while satisfying the users' preference.

4.3.1 AIR CONDITIONING CONTROLLER

The indoor temperature of a room with air conditioners can be modeled as follows, [29]:

$$T_{k+1} = T_k - \alpha q_k + \beta\left(T_k - T_k^{out}\right) = \left(1-\beta\right)T_k - \alpha q_k + \beta T_k^{out} \tag{4.13}$$

where

T_k	is the temperature inside the room (managed by the air conditioner), [^{0}C]
T_k^{out}	is the outdoor temperature, [^{0}C]
q_k	is the electricity consumed by the air conditioner, [kWh]
α	is the coefficient denotes the efficiency of the air conditioner, [^{0}C/kWh]
β	is the coefficient denotes the heat transferring between inside and outside of the room, [pu]

The problem is to minimize the electricity charge of the air conditioner while subject to a constraint that the room temperature must be kept within a certain range ($T_{min} \leq T_k \leq T_{max}$). Sometimes, the deviation from desired temperature (*e.g.* 24^{0}C) is included representing the comfort deterioration of the user. The objective function is formulated as follows.

$$\min_{\substack{q_k \\ k=1,\ldots,N}} \mathop{\mathrm{E}}_{\substack{\rho_k^e, T_k^{out} \\ k=1,\ldots,N}} \left\{ \sum_{k=1}^{N} \rho_k^{RT} q_k + \gamma \left(T_k - T_{ref} \right)^2 \right\} \tag{4.14}$$

where

T_{ref} is the user’s preference of temperature, [^{0}C]

γ is the coefficient denotes the cost of comfort deterioration, [\$/^{0}C^2]

The control policy can be derived analytically by DP backward algorithm as:

$$q_k^* = \frac{1}{\alpha} \left[\left(1-\beta\right) T_k - T_{ref} + \beta \overline{T}_k^{out} - \frac{1}{2\alpha\gamma} \left(\overline{\rho}_k^e - \left(1-\beta\right) \overline{\rho}_k^e \right) \right] \tag{4.15}$$

4.3.2 LIGHTING CONTROLLER

The lighting system problem can be modeled as follows [29].

$$Il_k = \alpha q_k \tag{4.16}$$

$$\min_{\substack{q_k \\ k=1,\ldots,N}} \mathop{\mathrm{E}}_{\substack{\rho_k^e \\ k=1,\ldots,N}} \left\{ \sum_{k=1}^{N} \rho_k^{RT} q_k + \gamma \left(Il_k - Il_{ref} \right)^2 \right\} \tag{4.17}$$

where

Il_k is the illumination of the lighting system, [lm]

Il_{ref} is the user’s preference of illumination, [lm]

α is the coefficient denotes the efficiency of lighting system, [lm/kWh]

γ is the cost of comfort deterioration, [\$/lm^2]

The control policy, again, derived analytically by DP backward algorithm is:

$$q_k^* = \frac{Il_{ref}}{\alpha} - \frac{1}{2\alpha^2\beta}\rho_k^e \tag{4.18}$$

4.4 ENERGY STORAGE SYSTEMS

Generally, Energy Storage Systems (ESSs) are used to store electricity during good times and reproduce it during the bad. While various technologies available such as flywheels, compressed air, or even hydrogen-storage, *etc.* batteries are the most widely used today. In this section, some applications of Battery Energy Storage (BES) in power systems are reviewed. It is shown that the scheduling of batteries (and other storage technologies) is fitting well to the DP framework.

4.4.1 BATTERY SCHEDULING IN STAND-ALONE SYSTEMS

In stand-alone systems, the scheduling of batteries and generating units is to minimize the total expected cost over a time horizon, *e.g.* a day, while supplying loads adequately.

$$\begin{aligned} \min_{\substack{u_k, I_{B,k} \\ k=1,\ldots N}} \; \underset{\substack{P_{Li,k}, P_{R,k} \\ k=1,\ldots N}}{\mathrm{E}} \Big\{ & \sum_{k=1}^{N} \sum_{i=1}^{N_G} c_{Gi}\left(P_{Gi,k}\right) + \\ & + u_{i,k} I\left(x_{i,k} < 0\right) S_i + \left(1 - u_{i,k}\right) I\left(x_{i,k} > 0\right) T_i \Big\}, \end{aligned} \tag{4.19}$$

subject to

$$\sum_{i=1}^{N_G} P_{Gi,k} + \sum_{i=1}^{N_R} P_{Ri,k} + P_{B,k} = \sum_{i=1}^{N_L} P_{Li} \tag{4.20}$$

where

$P_{B,k}$ is the power charging/discharging of BES at k-th stage, [MW]

$P_{Ri,k}$ is the power output of RES unit i at k-th stage, [MW]

$P_{Gi,k}$ is the power output of generator i at k-th stage, [MW]

$P_{Li,k}$ is the consumption of load i at k-th stage, [MW]

The electrical performance of BES can be modeled as follows:

$$SOC_{k+1} = SOC_k + I_{B,k}\Delta t \tag{4.21}$$

$$P_{B,k} = \begin{cases} I_{B,k}V_{B,ch}\left(SOC_k\right) & \text{if charging} \\ \\ I_{B,k}V_{B,dis}\left(SOC_k\right) & \text{if discharging} \end{cases} \tag{4.22}$$

where

SOC_k is the State Of Charge at k-th stage, [Ah]

$I_{B,k}$ is the charging/discharging current at k-th stage, [kA]

$V_{B,ch}$ is the charging voltage as a function of SOC, [kV]

$V_{B,dis}$ is the charging voltage as a function of SOC, [kV]

Δt is the stage duration, [hour]

Even the formulation in (4.20) seems as an extension of the unit commitment under monopoly industry, the existence of batteries and its electrical model make the problem highly nonlinear and the solution becomes much more complicated. In [12], a combined Lagrangian Relaxation (LR) and DP method is proposed for solving this problem.

4.4.2 BATTERY SCHEDULING UNDER MARKET ENVIRONMENTS

Under market environments, batteries are often used in coordination with renewable energy to provide the combined system with controllability. In this case, the interaction between batteries and the rest of the system is only through the market price. In [13], the scheduling of a combined battery and wind generation system for maximizing the total profit in both the balancing and spot market is presented. The formulation is as follows.

$$\max_{\substack{P_{B,k}\\k=1,\dots N}} \ \mathop{\mathrm{E}}_{\substack{P_{R,k}\\k=1,\dots MC}} \left\{ \sum\nolimits_{k=1}^{MC} \rho_k^{RT} \left(P_{B,k} + P_{R,k}\right) + \sum\nolimits_{k=MC+1}^{N} \rho_k^{SP} P_{B,k} \right\}, \tag{4.22}$$

where

[1 : MC] is the scheduling period of the balancing market (*e.g.* 4 hours)

[MC+1 : N] is the scheduling period of the spot market (*e.g.* 24 hours)

ρ^{RT}, ρ^{SP} are the real-time price and spot price respectively, [$/MWh]

$P_{B,k}$ is the dispatch of BES in k-th stage, [MW]

$P_{R,k}$ is the deviation from the contract of RES in k-th state, [MW]

CHAPTER V

MODELING OF BATTERY ENERGY STORAGE SYSTEMS

5.1 MODELING OF ELECTRICAL PROPERTIES

Basically, batteries consist of a bundle of cells connected in series, parallel, or a combination of both. Two electrodes, an anode and a cathode separated by an electrolyte, constitute each cell's active materials. When the cell is connected to loads, a reduction-oxidation reaction transfers electrons from the anode to the cathode. This transfer converts the chemical energy stored in the active material to electrical energy, which flows as a current in the external circuit.

5.1.1 ORIGINAL THEVENIN MODELS

Many study efforts have been spent for modeling of batteries base on the physical and chemical processes that occur in the battery. Some studies try to model the fundamental principle of thermodynamics, reaction kinetics and transport theory for both electrodes of batteries and for the whole cell [30]; however, these models are usually not suitable and useful for users due to complexity and a great number of parameters that need to be determined experimentally [31]. For this reason, electrical models based on Thevenin equivalent circuits are used. The model is simple but can provide sufficient insights of the electrical characteristic of batteries. The model consists of a voltage source, V_{OC}, connected to the external circuit through a series and a parallel resistor, R_S and R_P [Figure 5.1].

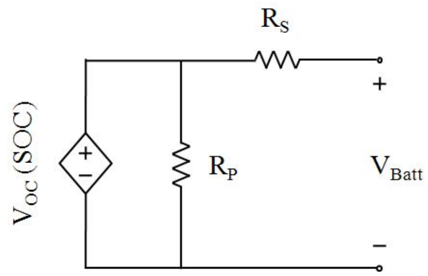

FIGURE 5.1 ORIGINAL THEVENIN MODEL OF BATTERIES

where, the series resistor represents the power loss of charging/discharging, and the parallel resistor represents the self-discharge effect (*i.e.* leakage current) within the battery.

In some studies, the open-circuit voltage (V_{OC}) is assumed to be constant, but some others provide the voltage model as a function of State Of Charge (SOC); this is called the steady-state voltage variation or DC response of batteries. The model is well-defined in MATLAB software.

$$V_{OC}\left(SOC\right) = E_0 - K\frac{Q}{Q-SOC} + Ae^{-B\cdot SOC} \tag{5.1}$$

where

E_0	is the constant voltage, [V]
K	is the polarization voltage, [V]
Q	is the battery capacity, [Ah]
A	is the exponential voltage, [V]
B	is the exponential capacity, [Ah^{-1}].

The SOC of batteries at time t = T is calculated as follows.

$$SOC(T) = SOC_0 - \int_{t=0}^{T} i(t)dt \tag{5.2}$$

where

SOC_0 is the initial SOC (at t = 0), [Ah]

i(t) is the charging/discharging current (Positive = discharging, Negative = charging), [A].

5.1.2 SIMPLIFIED THEVENIN MODELS

The steady-state voltage variation according to the Depth Of Discharge (DOD) of batteries can be expressed in Figure 5.2. The voltage variation can be divided into three areas: first, the voltage falls quickly (exponentially) as the DOD increases; secondly, the voltage decreases slower (nearly linear) until the minimum allowable SOC is reached (at the nominal voltage); and lastly, the battery voltage decays rapidly when discharging over the limits.

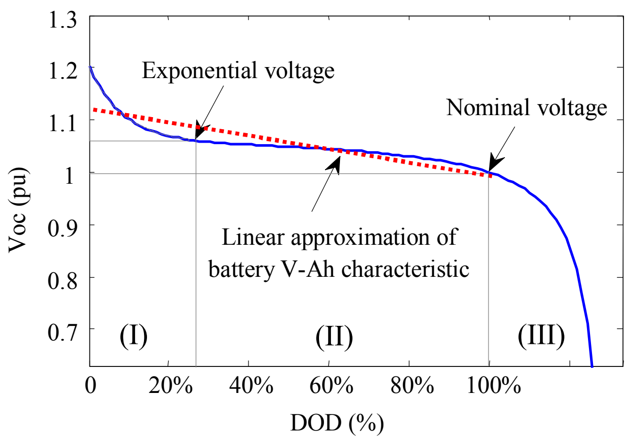

FIGURE 5.2 STEADY-STATE VOLTAGE VARIATION OF BATTERIES AND THE APPROXIMATE LINEAR MODEL

Even the model in (5.1) is clear and simple; the nonlinearity inherent in the circuit model and the internal voltage causes a huge computation in the optimization problem. In addition, from the economic point of view, it is not necessary to model batteries in all events, such as out of the limit (*i.e.* the area 3). Therefore, in this study, we propose a linear approximation of the battery voltage in normal operation (as expressed by dashed-line in Figure 5.1)

$$V_{OC}\left(SOC\right) = E_0^{'} + K^{'}SOC \tag{5.3}$$

where the coefficients of the simplified model, $E_0^{'}$ and $K^{'}$, can be determined using fitting techniques available in MATLAB.

The power loss and self-discharge current of batteries can be calculated from the Thevenin equivalent circuit as follows.

$$P_{Loss} = \frac{V_{OC}^2\left(SOC\right)}{R_P} + I_{Batt}^2 R_S \tag{5.4}$$

$$I_{selfdischarge} = \frac{V_{OC}\left(SOC\right)}{R_P} \tag{5.5}$$

where

P_{Loss} is the power loss of batteries, [W]

I_{Batt} is the current drawn from the battery, [A]

R_S, R_P are the series and parallel resistor, [Ohm].

5.2 MODELING OF ECONOMIC PROPERTIES

5.2.1 BATTERY LIFETIME MODELS

Generally, the lifetime of a battery bank is given by manufacturers, either in term of Ah-through or life-cycles, which indicates the theoretical amount of charging units (*i.e.* ampere-hour) or the number of cycles that the battery can achieve before dying out. The matter of fact is that these lifetimes are often determined by various testing methods and under certain conditions which may be very different from practice. Indeed, the operating condition of batteries in power systems is characterized by partial SOC, incomplete or rare full of charge, and a wide range of ambient temperature. In [34] and [35], six important stress factors are defined which link the operating condition with the lifetime of a battery bank; including charge factor, Ah-throughput, time between full of charges, time at low SOC, and temperature. It is worth noting that these factors can physically reduce the rate of one aging process but increase the rate of another. For example, a high temperature will accelerate the rate of corrosion, but decrease the rate of formation of hard irreversible sulphation products in lead-acid batteries [35]. Therefore, quantifying the influence of the stress factors on the lifetime of a whole battery bank needs a thorough understanding and analysis of the aging process.

In order to estimate the lifetime of batteries, three approaches have been proposed [36]-[38]. The first approach, called performance-based model, is based on the simulation of each aging process as a function of operating conditions and changes of the battery performance while the aging processes take place. The battery is said to be at end-of-life if its performance value crosses a threshold. This method takes advantage of accuracy, but suffers from a huge computation, hence, cannot be used in the real-time application. The second approach, called Ah-throughput model, is based on an assumption that once a predetermined amount of Ah put through (*i.e.* charging and discharging) the battery, it is at end-of-life. For taking into account the impact of operating conditions, weighted factors are added, hence, called weighted Ah-throughput model. Lastly, the third approach, called event-oriented model, is based on an assumption that incremental losses of the lifetime caused by different events are added up until a certain value is reached. Thus, in some sense, this approach shares a similar principle with the Ah-throughput model.

5.2.2 BATTERY COST FORMULATION

In power system applications, a number of batteries are connected in series and parallel for providing electric power at a sufficient voltage and current, *i.e.* battery bank. As the lifetime of batteries is quite short, its lifetime and replacement cost, C_{rep}, are the most important factors from economic perspectives. In this study, the weighted Ah-throughput model is used for evaluating the operating cost of batteries. For a given Battery Energy Storage (BES), the cost associated with a theoretical Ah-throughput (*i.e.* roundtrip of a charging unit), called battery wear cost, can be evaluated as follows [39].

$$c_{bw} = \frac{C_{rep}}{N \cdot Q_{lifetime}} \tag{5.6}$$

where

c_{bw} is the battery wear cost, [$/Ah]

N is the number of batteries in the bank

$Q_{lifetime}$ is the theoretical lifetime of each battery, [Ah]

As aforementioned, $Q_{lifetime}$ is obtained by various testing methods and under certain conditions. However, the actual operating condition is usually very different from the test, and any deviations can result in a virtual increase (or decrease) in the battery lifetime. The impact of operating conditions is modeled in [37], as follows.

$$f_{SOC} = 1 + \left(c_{SOC,0} + c_{SOC,\min}\left(1 - SOC_{\min}\right)\right) f_I\left(I, n\right) \Delta t_{SOC} \tag{5.7}$$

where

f_{SOC} is the impact of SOC

$f_I(I,n)$ is the impact of battery currents

$c_{SOC,0}$ is the coefficient represents the impact when SOC = 0

$c_{SOC,min}$ is the coefficient represents the impact at lowest SOC, [h^{-1}]

SOC_{min} is the lowest SOC since the last full charge, [pu]

Δt_{SOC} is the time since the last full charge, [h].

The current factor is calculated as follows.

$$\begin{aligned} f_I\left(I, n\right) &= f_I\left(I\right) \sqrt[3]{e^{n/3.6}} \\ &= \sqrt{\frac{I_{Ref}}{I_{Batt}}} \cdot \sqrt[3]{e^{n/3.6}} \end{aligned} \tag{5.8}$$

where

I_{Ref} is the reference current of the battery, [A]

I_{Batt} is the actual battery current, [A]

n is the number of bad recharges (SOC > SOC_{max}), which indicates the sulfate-crystal impact of the electrodes (lead-acid battery).

Assuming batteries are kept within the limits during operation, some factors can be excluded from our consideration: bad recharge and $c_{SOC,0}$. Then, the impact of SOC, current and time (between full charges) can be combined as:

$$f_{SOC} = 1 + c_{SOC,\min}\left(1 - SOC_{\min}\right)\Delta t_{SOC}\sqrt{\frac{I_{Ref}}{I_{Batt}}} \tag{5.9}$$

The cost associated with an Ah-throughput under operating conditions can be estimated as follows.

$$c_{Batt} = c_{bw}\left(1 + c_{SOC,\min}\left(1 - SOC_{\min}\right)\Delta t_{SOC}\sqrt{\frac{I_{Ref}}{I_{Batt}}}\right) \tag{5.10}$$

where

c_{Batt} is the battery cost, [$/Ah]

The formulation in (5.10) implies that the batter cost is higher when operating at low SOC, small battery currents, and long duration between full charges. Physically, these factors cause tresses on the active masses and increase the size of sulfate crystal in lead-acid batteries, consequently reducing its lifetime.

CHAPTER VI

ECONOMIC OPERATION OF INDEPENDENT BATTERY ENERGY STORAGE SYSTEMS IN REAL-TIME MARKETS

6.1 PROBLEM STATEMENT

In this problem, we consider the case of an independent Battery Energy Storage System (BESS) operating in real-time markets. The owner can control BESS in response to the market price (*i.e.* real-time price) to make profits. Thus, the problem is to maximize the total profit in a day [Figure 6.1].

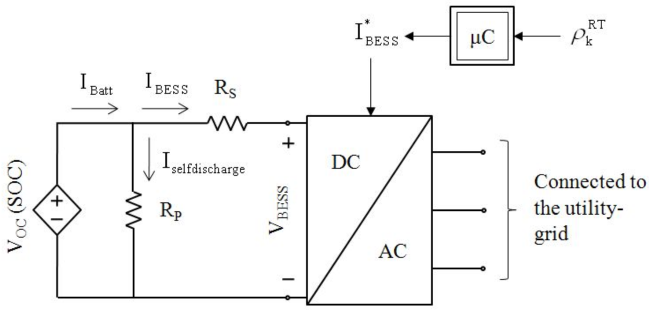

FIGURE 6.1 BATTERY ENERGY STORAGE SYSTEM IN REAL-TIME MARKETS

6.2 MATHEMATICAL FORMULATION

The profit consists of the revenue from real-time markets and the cost of using batteries. Thus, the objective function can be formulated as follows.

$$\max_{\substack{I_{BESS}[k] \\ k=1,\dots N}} \left\{ P_{BESS}[k]\Delta T \cdot \rho_k^{RT} - Ah[k] \cdot c_{Batt}\left(SOC[k], I_{BESS}[k], \Delta t_{SOC}[k]\right) \right\} \quad (6.1)$$

$$V_{OC}[k] = E_0^{'} + K^{'} SOC[k] \tag{6.2}$$

$$I_{Batt}[k] = I_{BESS}[k] + \frac{V_{OC}(SOC[k])}{R_P} \tag{6.3}$$

$$P_{BESS}[k] = I_{Batt}[k] \cdot V_{OC}(SOC[k]) - I_{BESS}^2[k] R_S - \frac{V_{OC}^2(SOC[k])}{R_P} \tag{6.4}$$

$$Ah[k] = \max(0, I_{Batt}[k]\Delta T) \tag{6.5}$$

Subject to

$$SOC[k+1] = SOC[k] - I_{Batt}[k]\Delta T \tag{6.6}$$

$$SOC_{\min} \le SOC[k] \le SOC_{\max} \tag{6.7}$$

$$I_{\min} \le I_{Batt}[k] \le I_{\max} \tag{6.8}$$

$$\begin{cases} SOC[0] = SOC_I \\ SOC[N] = SOC_F \end{cases} \tag{6.9}$$

where

I_{BESS} is the charging/discharging current of the whole BESS, [A]; (Positive = discharging, Negative = charging)

P_{BESS} is the power output of the whole BESS [kW]

ΔT is the time basis of real-time markets, [h];

ρ^{RT} is the real-time price, [$/kWh]

"Ah" is the amount of Ah discharged from the BESS, [Ah]

SOC_{max} is the maximum SOC of the BESS, [Ah]

SOC_{min} is the minimum SOC of the BESS, [Ah]

I_{min} is the minimum current of the BESS, [A]

I_{max} is the maximum current of the BESS, [A]

SOC_I is the initial SOC of the BESS, [Ah]

SOC_F is the ending SOC of the BESS, [Ah]

In the above formulation, the objective function in (6.1) is the accumulated profit in a day including the market revenue (first term) and the battery cost (second term); (6.2) denotes the open-circuit voltage as a function of SOC; (6.3) indicates the battery charging/discharging current with the self-discharge effect; (6.4) is the calculation of BESS power output with the power losses; (6.5) expresses the Ah throughput (only when discharging); (6.6) shows SOC transition; (6.7) and (6.8) represent the capacity limits of BESS. It is noted that the battery cost is only accounted in the discharging stage (*i.e.* charging units complete a roundtrip); otherwise, the battery cost is zero. Finally, (6.9) expresses the initial and final state constraint, *i.e.* BESS is required to stay at a specified state at beginning and ending of the scheduling horizon.

6.3 DETERMINISTIC DYNAMIC PROGRAMMING

The solution of the above-formulated problem suffers from some difficulties. First, the inclusion of battery models has made the problem at high nonlinearity. Secondly, the inter-correlation of BESS decisions rather makes the problem complicated (*i.e.* the decision at each stage will affect the optimality in future). For this reason, DP is one of the most suitable and promising methods. The deterministic DP framework for the problem is presented in Figure 6.2.

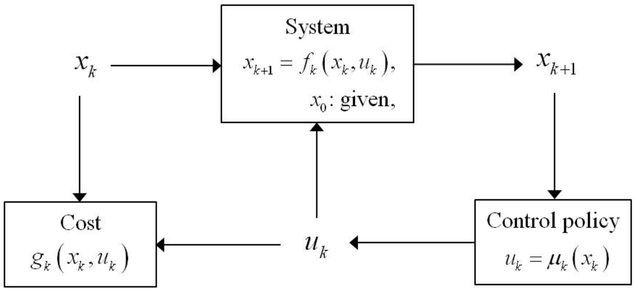

FIGURE 6.2 DETERMINISTIC DYNAMIC PROGRAMMING FRAMEWORK

Let us define variables in the deterministic DP framework:

- State variable: x_k is the SOC of BESS at the beginning of stage k
- Control variable: u_k is the charging/discharging current of BESS during stage k

The system model, $f_k(x_k, u_k)$, is the SOC transition in (6.6), and the cost function, $g_k(x_k, u_k)$, is minus of the profit in (6.1). The problem is to determine the control policy, $\pi^* = \{\mu_0^*, \mu_1^*, \dots \mu_{N-1}^*\}$, *i.e.* a set of functions which gives the optimal decision for a given system state: $u_k^* = \mu_k^*(x_k)$ [40].

The DP backward algorithm is used for solving this problem. The algorithm starts from the last stage and moves backward to the initial stage to find the control policy, *i.e.* optimal solution for a given system state at each stage. A performance index called cost-to-go function of the algorithm is defined as follows.

$$\begin{Bmatrix} J_N(x_N) = 0 \\ J_k(x_k) = \max_{u_k} \{ g_k(x_k, u_k) + J_{k+1}(x_{k+1}) \}, \\ \hfill k = 0, 1, \dots N-1 \end{Bmatrix} \tag{6.9}$$

With the time basis of real-time markets is 5 minutes, the number of stages of the problem is $N = 24 \times 12 = 288$ stages over a day. This algorithm, in turn, guarantees the optimality of the solution.

6.4 CASE STUDY

There is a matter of fact that today the cost of batteries is extremely high compared to the electricity price; if this cost is considered, there is no point to use BESS in electricity markets. Therefore, this study mainly focuses on analyzing the sensitivity of profits to the battery cost; at the same time, provides some insights of the economic operation of batteries considering operating conditions.

6.4.1 BASE CASE OPERATION

Considering an independent BESS working in real-time markets for profits, the parameter of BESS is given in Table 6.1.

TABLE 6.1 PARAMETERS OF BATTERY ENERGY STORAGE SYSTEM IN THE BASE CASE

Battery models		**Capacity limits and costs**	
E_0 (kV)	1.2645	V_{nom} (kV)	1.2
K (kV/Ah)	0.0033	I_{ref} (kA)	10
A (kV)	0.066	SOC_{max} (10^3Ah)	50
B (Ah^{-1})	250	SOC_{min} (10^3Ah)	10
R_S (ohm)	0.065	$c_{SOC,min}$ (h^{-1})	0.035
R_P (ohm)	$1.25 \cdot 10^3$	c_{bw} (\$/Ah)	0.0065

The steady-state voltage variation and its simplified (linear) model are displayed in Figure 6.3. The coefficients of the simplified model are obtained using Least Mean Square (LMS) technique available in MATLAB.

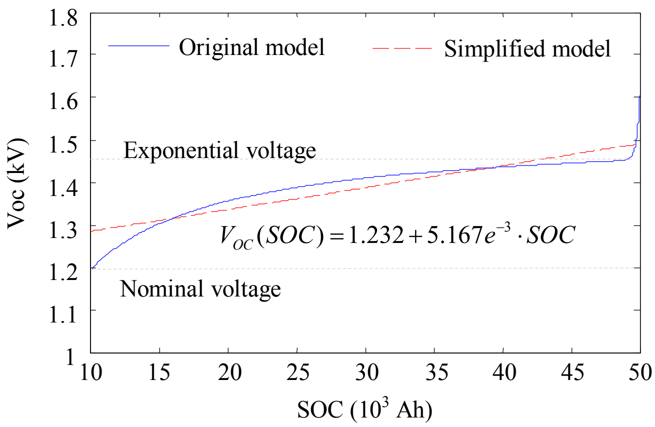

FIGURE 6.3 THE STEADY-STATE VOLTAGE VARIATION AND SIMPLIFIED MODEL

It is assumed that BESS is required to stay at low SOC ($20 \cdot 10^3$Ah) in midnight for taking advantages of low electricity price during night times. The numerical simulation result of BESS operation in response to the real-time price (ρ^{RT}) is displayed in Figure 6.4, including BESS current, I_{BESS}, and SOC.

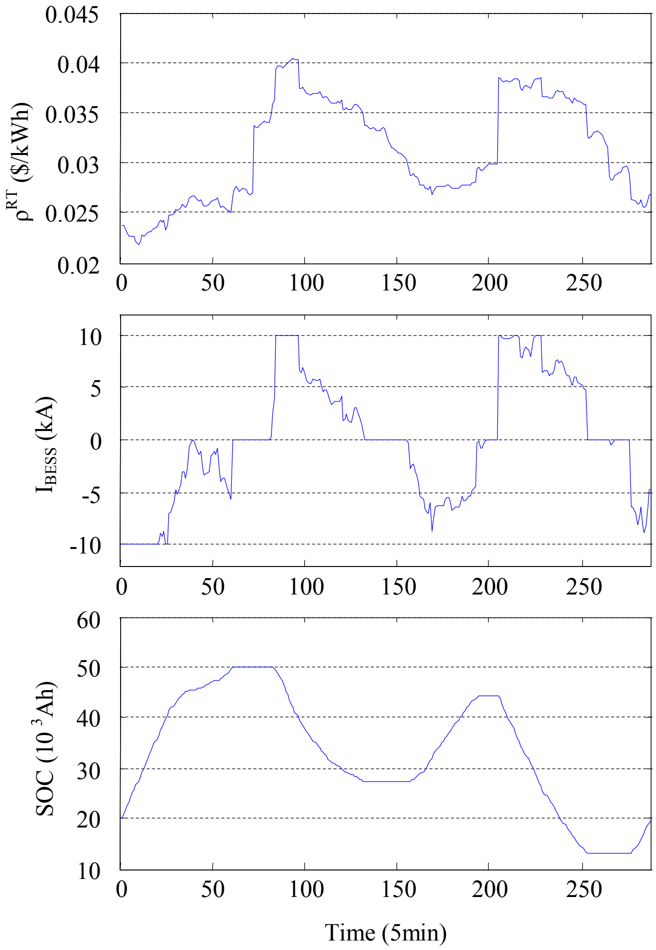

FIGURE 6.4 THE NUMERICAL SIMULATION RESULT IN THE BASE CASE

Figure 6.4 shows that BESS properly responds to the variation of the real-time price: BESS charges (consume electricity) during the low price time, [00:00 – 05:00], [12:30 – 14:00] and [23:00 – 24:00], and discharges (re-produce) when the price is high, [07:30 – 10:00] and [16:30 – 20:30]. Other times, BESS is in standby because the discrepancy of the real-time price is not sufficient to cover the battery cost. In addition, the capacity limits and the initial and final state constraints of BESS are maintained during operation.

The real-time price in this simulation is achieved by modifying the spot price of PJM electricity market [50].

6.4.2 VALIDITY OF THE SIMPLIFIED MODEL

In simplified models, the open-circuit voltage (V_{OC}) of BESS is approximated as a linear function of SOC. The error of this approximation, *i.e.* difference between the simplified model and the original Thevenin model, are presented in Figure 6.5. It is shown that a large error occurs when BESS is at maximum SOC, [5:00 – 7:00]. This is because when SOC approaches SOC_{max}, V_{OC} increases exponentially with the original model, while it is linear in the simplified model. Fortunately, this only occurs when BESS operates closely the maximum SOC; otherwise, the error is small; the power output, P_{BESS}, and the profit are close between two models. In this case simulation, the total profit calculated with the original model is $364.922, and that with the simplified model is $361.012. The difference is about 1%. The statistics of the error are summarized in Table 6.2.

TABLE 6.2 THE STATISTICS OF THE ERROR BETWEEN SIMPLIFIED AND ORIGINAL MODELS

Errors	Min.	Max.	Mean	Std. dev.	Range
ΔV_{OC} (kV)	-0.03276	0.1171	0.01113	0.03688	0.1498
ΔP_{BESS} (MW)	-0.323	0.258	0.0009	0.1044	0.5818
ΔProfit ($)	-1.068	0.829	0.1473	0.2795	1.897

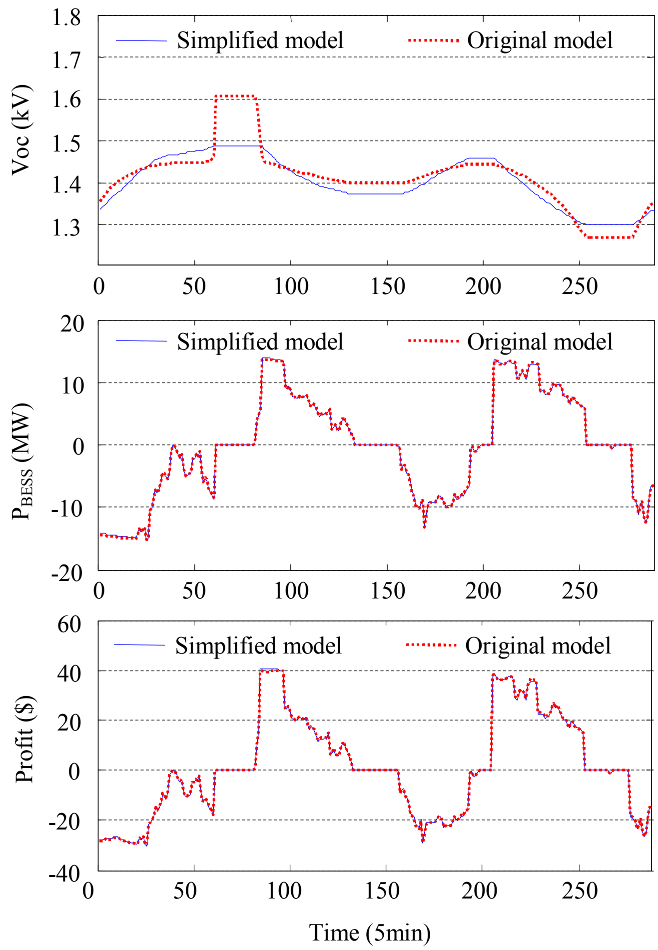

FIGURE 6.5 THE DIFFERENCE BETWEEN SIMPLIFIED AND ORIGINAL MODELS

6.4.3 SENSITIVITY ANALYSIS

The optimal operation and profit of BESS is not only dependent on the market price but also the battery wear cost (c_{bw}). If c_{bw} is low, BESS should be used (*i.e.* charging and discharging) more frequently according to the variation of the market price. In contrast, if c_{bw} is high, BESS is only used once the discrepancy of the market price is large enough to cover the battery cost. The optimal operation of BESS in different cases with c_{bw} = 0, 1, and 3 times of the base case (C_{base} = 0.0065$/Ah) are presented in Figure 6.6. Case 1 (c_{bw} = 0$/Ah) is the scheduling of BESS without consideration of battery costs as the studies in [12] and [13]. The problem is only maximizing the revenue from electricity markets; thus BESS is charged and discharged continuously as the variation of the market price. In case 3, when the battery wear cost is high ($c_{bw} = 3C_{base}$), the profit only can be achieved when charging at the valley, [00:00 – 02:00], and discharging at the peak of the real-time price, [07:30 – 09:30]; the use of BESS is very limited.

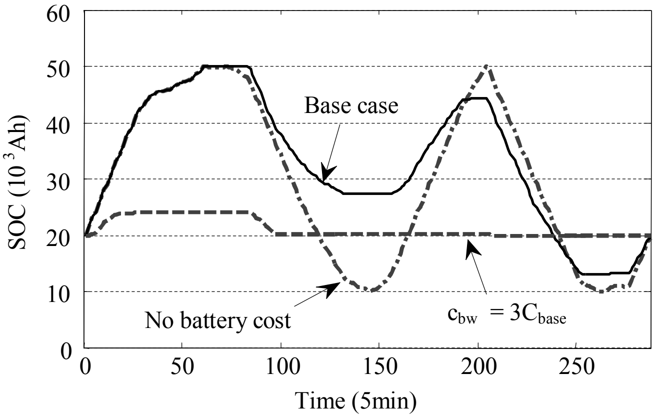

FIGURE 6.6 THE ECONOMIC OPERATION WITH RESPECT TO BATTERY WEAR COSTS

The change of BESS profits according to the battery wear cost is presented in Figure 6.7. It is shown that the profit of BESS falls down as battery wear cost increases, and at $c_{bw} = 3C_{base}$, a very small profit can be obtained ($6.283).

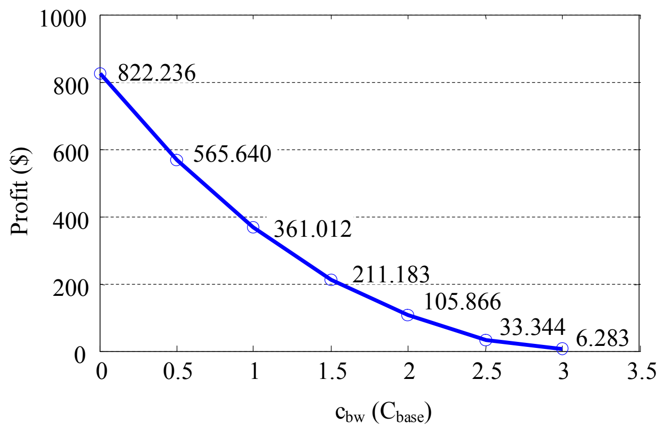

FIGURE 6.7 THE PROFIT ACCORDING TO BATTERY WEAR COSTS

CHAPTER VII

ECONOMIC OPERATION OF COMBINED BATTERY WIND GENERATION SYSTEMS IN REAL-TIME MARKETS

7.1 PROBLEM STATEMENT

Under market environments, Wind Power Producers (WPPs) may lose benefits since their peak generation usually occurs at night times when the market price is low. Also, WPPs face many regulation charges due to the intermittence of outputs and contracting errors in day-ahead markets. This issue can be resolved by combining wind generation with Battery Energy Storage (BES) for managing the output of the overall system. In this chapter, we propose a framework for the economic operation of combined Battery Wind Generation Systems (BWGS) in real-time markets. The problem is to maximize the total profit considering both market revenues and battery costs in a day. The scheduling of BES is not only based on the market price (*i.e.* real-time price), but also the uncertainty of wind generation, *i.e.* real-time deviation. Therefore, in this case, a stochastic Dynamic Programming (DP) framework is used where the wind uncertainty is modeled as a random variable. It is noted that the bidding of WPPs in day-ahead markets is out of the scope of this study; and without losing generality, the mean value is assumed to be contracted.

7.2 MATHEMATICAL FORMULATION

The case of WPPs operating in real-time markets for profits is presented in Figure 7.1.

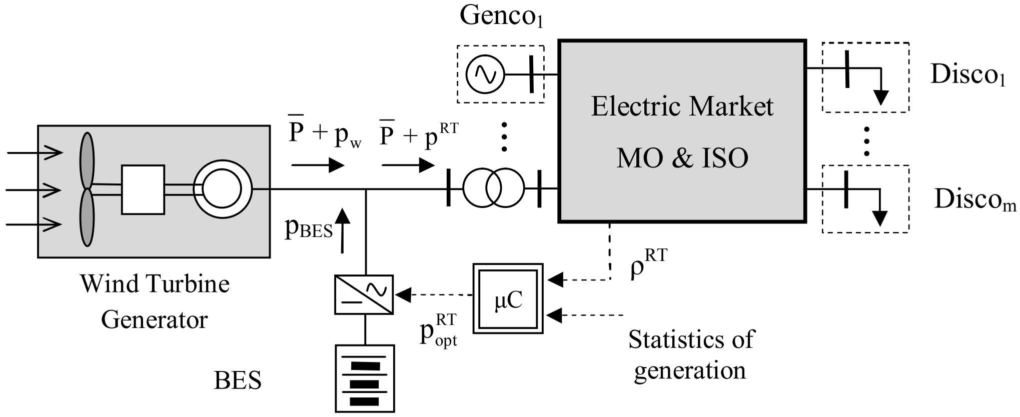

FIGURE 7.1 WIND POWER PRODUCERS IN REAL-TIME MARKETS

where

$\overline{P}$ is the day-ahead contract of WPP, [MW]

p_w is the real-time variation of wind generations, [MW]

p_{BES} is the real-time charging/discharging power of BES, [MW], (Positive = Discharging; Negative = Charging)

p^{RT} is the real-time generation of the overall BWGS, [MW]

p_{opt}^{RT} is the optimal real-time generation of the overall BWGS, [MW]

ρ^{RT} is the real-time price, [\$/MWh]

The stochastic model of wind generations will be discussed later in this chapter. It is noted that BES in this study takes two important tasks:

1. Absorbing the real-time deviation (*i.e.* uncertainty) of wind generations caused by the variation of resources: wind speed, temperature, *etc.*
2. Charging/discharging in response to the market price (*i.e.* real-time price) to make profits.

The profit of WPPs in each stage comprised of market revenues and battery costs can be calculated as follows.

$$\Pi_k = p^{RT}[k]\Delta T \cdot \rho_k^{RT} - Ah[k] \cdot c_{Batt}\left(SOC[k], P_{BES}[k], \Delta t_{SOC}[k]\right) \quad (7.1)$$

In (7.1), the first term denotes the revenue from real-time markets, while the second term denotes the battery cost used by WPPs. The charging/discharging power of BES is dependent on the actual deviation of wind generations:

$$p_{BES}[k] = p^{RT}[k] - p_w[k] \quad (7.2)$$

The BES voltage, current and Ah-throughput can be calculated as follows.

$$I_{Batt}[k] = \frac{p_{BES}[k]}{V_{BES}[k]} + I_{selfdischarge} \quad (7.3)$$

$$Ah[k] = \max\left(0, I_{Batt}[k]\Delta T\right) \quad (7.4)$$

The objective function and constraints of the problem can be formulated as follows.

$$\max_{\substack{p^{RT}[k] \\ k=1,2\ldots288}} \; \mathop{\mathrm{E}}_{\substack{p_w[k] \\ k=1,2\ldots288}} \left\{ \begin{array}{l} \sum_{k=1}^{288} p^{RT}[k]\Delta T \cdot \rho_k^{RT} - \\ \qquad Ah[k] \cdot c_{Batt}\left(SOC[k], P_{BES}[k], \Delta t_{SOC}[k]\right) \end{array} \right\} \quad (7.5)$$

Subject to

$$SOC[k+1] = SOC[k] - I_{Batt}[k]\Delta T \quad (7.6)$$

$$SOC_{\min} \le SOC[k] \le SOC_{\max} \quad (7.7)$$

$$I_{\min} \leq I_{Batt}[k] \leq I_{\max} \tag{7.8}$$

$$\begin{cases} SOC[0] = SOC_I \\ SOC[N] = SOC_F \end{cases} \tag{7.9}$$

where

ΔT is the time basis of real-time markets, [h]

SOC_{max} is the maximum SOC of BES, [Ah]

SOC_{min} is the minimum SOC of BES, [Ah]

I_{min} is the minimum current of BES, [A]

I_{max} is the maximum current of BES, [A]

SOC_I is the initial SOC of BES, [Ah]

SOC_F is the final SOC of BES, [Ah]

The objective function in (7.5) denotes the cumulative profit of WPPs over a day with the expectation of the wind uncertainty; ΔT is the time basis of real-time markets, (5 minutes). The payment for contracting error in day-ahead (spot) markets, $\rho^{RT}(\overline{P} - P^{DA})$, is independent from the real-time generation, thus, it is can be excluded from the formulation. Equation (7.6) shows the SOC transition of BES which is affected by wind uncertainties. Equations (7.7) and (7.8) represent the capacity and current limits of BES. Finally, (7.9) shows the constraint of the initial and final state of BES.

7.3 STOCHASTIC DYNAMIC PROGRAMMING

As the above formulation, the operation of BES in this problem not only depends on the market price (ρ_k^{RT}) but also the uncertainty of wind generation (p_w). In more details, the system state (SOC) is no longer deterministic as the case of independent BESS (Chapter VI), but changing stochastically according to the deviation of wind outputs. Therefore, in this problem, the stochastic DP framework is used for solution with the wind uncertainty is modeled as a random variable. The stochastic DP framework is sketched in Figure 7.2.

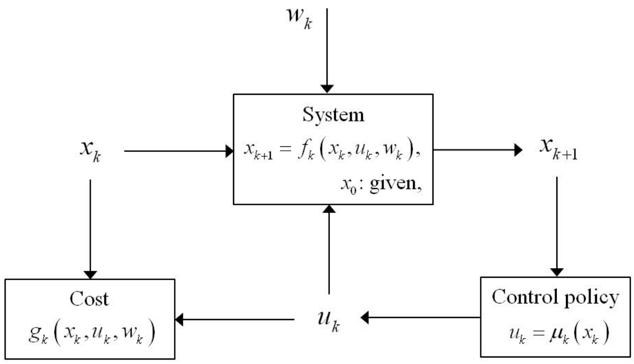

FIGURE 7.2 STOCHASTIC DYNAMIC PROGRAMMING FRAMEWORK

Let us define variables in the stochastic DP framework:

- State variable: x_k is the SOC of BES at the beginning of stage k
- Control variable: u_k is the charging/discharging current of BES during stage k
- Random variable: w_k is the deviation of wind generation in stage k

The system model, $f_k(x_k, u_k, w_k)$, represents the SOC transition function of BES in (7.6), and the cost function, $g_k(x_k, u_k, w_k)$, is minus of the profit in (7.5). The solution is to determine the control policy, $\pi^* = \{\mu_0^*, \mu_1^*, \dots \mu_{N-1}^*\}$, *i.e.* a set of functions of the system state which gives the optimal decision for a given system state: $u_k^* = \mu_k^*(x_k)$ [40].

Again, the DP backward algorithm is used for solving this problem. The algorithm starts from the last stage and move backward to the initial stage to find the optimal solution for a given system state at each stage. A performance index, *i.e.* cost-to-go function, of the algorithm is defined as follows.

$$\left\{\begin{array}{l} J_N(x_N)=0 \\ J_k\left(x_k\right)=\max\limits_{u_k}\underset{w_k}{E}\left\{g_k\left(x_k,u_k,w_k\right)+J_{k+1}\left(x_{k+1}\right)\right\}, \\ \hfill k=0,1,\ldots N-1 \end{array}\right\} \tag{7.10}$$

With the time basis of real-time markets is 5 minutes, the number of stages of the problem is $\mathrm{N}=24\times 12=288$ stages over a day. This algorithm, in turn, guarantees the optimality of the solution.

The optimal policy indicates the off-line scheduling of WPPs; for each stage, the optimal decision is a function of the system state (*i.e.* SOC). The on-line (*i.e.* real-time) operation depends on the current state and combines with the off-line schedule to determine the optimal control. This scheme maximizes the expected profit of WPPs with respect to the various scenario of wind generation.

7.4 CASE STUDY

7.4.1 SYSTEM CONFIGURATION

Assuming the same amount of BES (Chapter VI) operating in combination with wind generation system, *i.e.* BWGS, the outline of the problem is sketched in Figure 7.1. The parameters of BES are in Table 7.1.

TABLE 7.1 THE PARAMETERS OF BATTERY ENERGY STORAGE

Battery model		Capacity limit and cost	
E_0 (kV)	1.2645	V_{nom} (kV)	1.2
K (kV/Ah)	0.0033	I_{ref} (kA)	10
A (kV)	0.066	SOC_{max} (10^3Ah)	50
B (Ah^{-1})	250	SOC_{min} (10^3Ah)	10
R_S (ohm)	0.065	$c_{SOC,min}$ (h^{-1})	0.035
R_P (ohm)	$1.25 \cdot 10^3$	c_{bw} (\$/Ah)	0.0065

The statistics of wind uncertainties is expressed in term of the prediction percentiles in Figure 7.3.

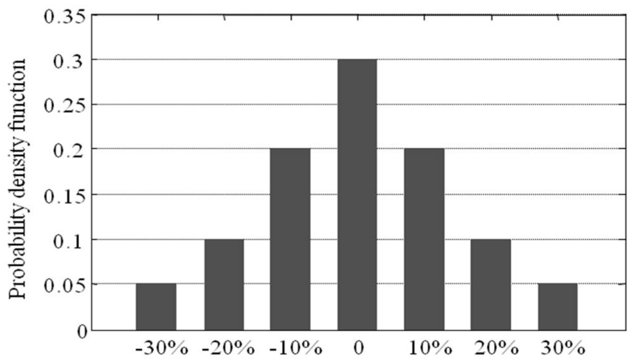

FIGURE 7.3 THE STATISTICS OF THE WIND GENERATION UNCERTAINTY

Figure 7.4 displays the spot price (blue, solid-line) and the real-time price (red, dashed-line). It is showing that sometimes the real-time price is higher than the spot price but lower in other times. This is because in upper cases when the system demand exceeds the supply, Independent System Operator (ISO) will order up regulation to increase generation in the overall system (*i.e.* ρ^{RE} will be positive), consequently, the real-time price will be larger than the spot price. In contrast, in lower cases, down regulation is needed; this results in the lower real-time price than the spot price.

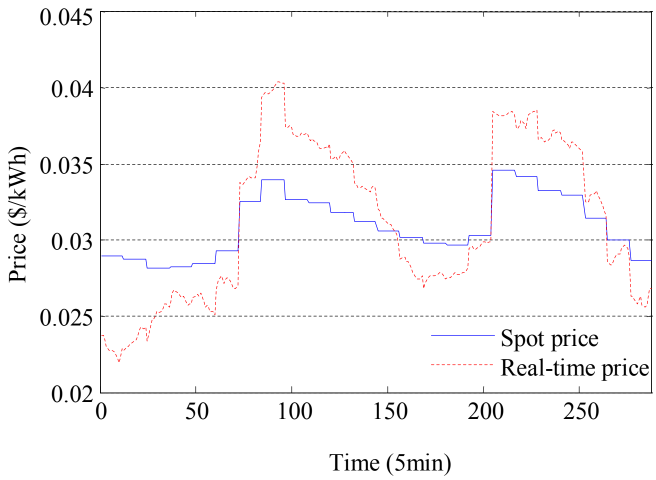

FIGURE 7.4 THE SPOT PRICE AND REAL-TIME PRICE

7.4.2 SIMULATION RESULTS

The simulation result is presented in Figure 7.5 and Figure 7.6.

The first graph in Figure 7.5 shows the actual generation of wind power and the contracted amount in day-ahead spot markets; other graphs show the optimal dispatch of BWGS and the profit during the day. It can be seen that BWGS properly responds to the market price, *i.e.* consuming electricity when the price is low and re-produce it when the price is high for profits.

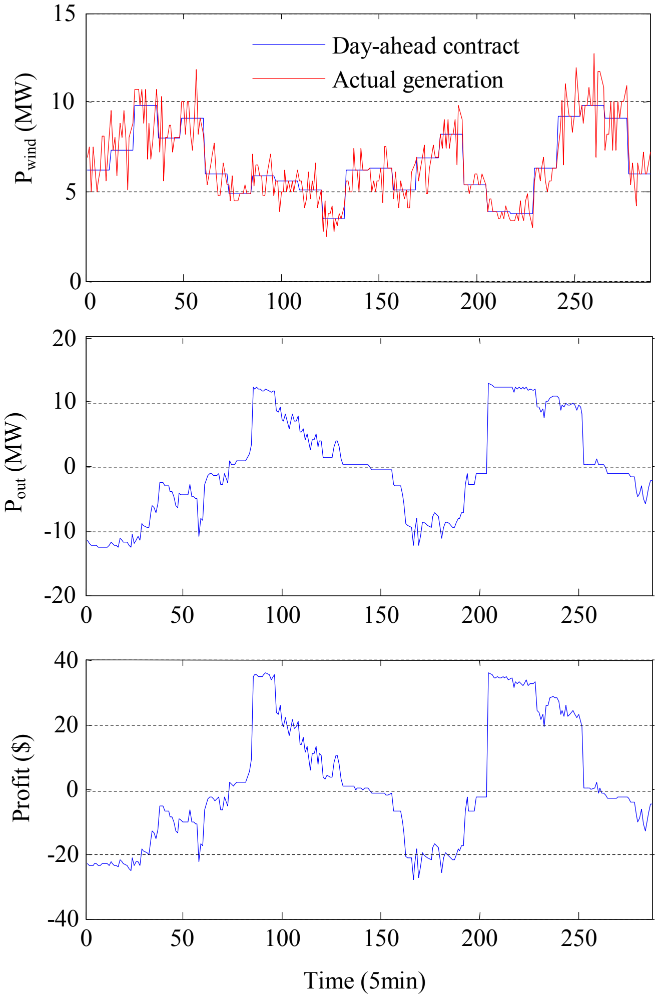

FIGURE 7.5 THE WIND GENERATION, OPTIMAL DISPATCH AND PROFIT

Figure 7.6 shows the performance of BES, including the charging/discharging current, SOC and the output voltage. The ripple in the graphs (especially with the current and voltage of BES) is because of the wind uncertainty. In this case, BES usually does not operate with the entire capacity; instead, a part of BES needs to spend for absorbing the wind uncertainty, controlling the overall output of BWGS while keeping BES within its physical limits.

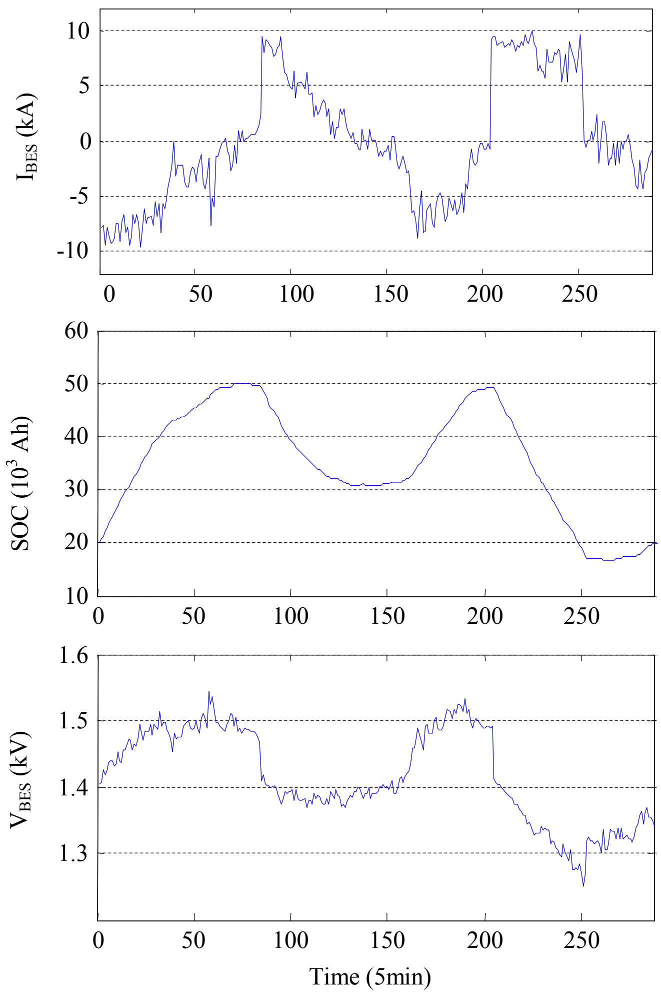

FIGURE 7.6 THE BES PERFORMANCE ACCORDING TO WIND GENERATIONS

7.4.3 COMPARISON AND DISCUSSION

In this section, we will compare the problem that BES and wind generation are in combination to the case where they operate separately. The optimal operation of an independent BES in real-time markets is presented in Chapter VI; in this problem, the entire capacity of BES can be used in response to the real-time price for profits, in turn, making a greater profit for WPPs ($361.01). However, the wind generation alone needs to pay for their deviation from the contracted in day-ahead markets; this charge is according to the real-time price. The imbalance cost is calculated through the payment scheme of real-time markets (Chapter II). In this study, the imbalance cost of WPPs is \$52.26. Therefore, the total profit in the case of separation (\$308.75) is smaller than the combination (\$321.5). The detail costs are displayed in Table 7.2.

TABLE 7.2 COMPARISONS BETWEEN COMBINED AND SEPARATE OPERATIONS

OPERATION STRATEGY	PROFIT	IMBALANCE COST	TOTAL
Combined operation	\$321.5	\$0	\$321.5
Separate operation	\$361.01	\$52.26	\$308.75

CHAPTER VIII

A NEW BATTERY CHARGING/DISCHARGING SCHEME FOR WIND POWER IN FREQUENCY CONTROL MARKETS

8.1 PROBLEM STATEMENT

This chapter proposes another battery approach for improving the value of wind power assuming the implementation of markets for frequency control. In this problem, BES is used to manage the variation of wind power, *i.e.* variation band, reducing the payment for frequency control of WPPs. In some sense, the problem is tradeoff between the frequency control payment and the battery cost, *i.e.* the more BES is used, the lower market payment but higher battery cost, and vice versus.

8.2 BATTERY MANAGEMENT SYSTEM

In order to moderate the operating condition in renewable energy systems and improve the lifetime of batteries, Battery Management System (BMS) has been proposed. The idea is to split the battery bank of BES into several strings connected in parallel via switches. Each string can be controlled individually; by thus the standard operating condition is nearly achieved [34]. The circuit concept of BMS is shown in Figure 8.1.

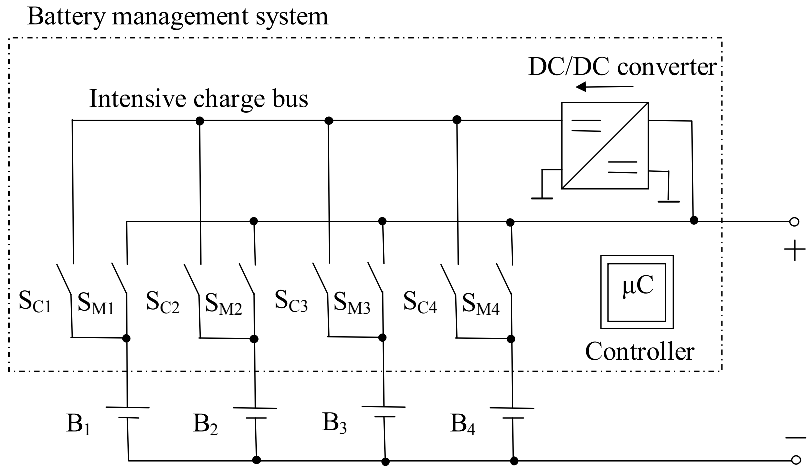

FIGURE 8.1 CIRCUIT CONCEPT OF BMS WITH FOUR PARALLEL SWITCHED BATTERY STRINGS (B1-B4)

In Figure 8.1, the entire battery bank of BES is divided into four parts (strings) which are connected in parallel via the main switches S_{M1}-S_{M4}. This provides the option of connecting or disconnecting the individual strings (B_1-B_4) independently from each other; by this means, some battery can be charged or discharged while the others do not have to be involved. In addition, BMS includes a DC/DC converter connected to DC bus through switches S_{C1}-S_{C4}. This component is to perform a full charge for individual battery strings when the available energy is not enough for full charge of the entire battery bank. Therefore, during normal operation in renewable systems, BMS enables shorter cycles at low SOC, increase in the current rate and intensive full charge; those are major stress factors on the lifetime of batteries [35].

8.3 MATHEMATICAL FORMULATION

The outline of WPPs in markets for frequency control is sketched in Figure 8.2.

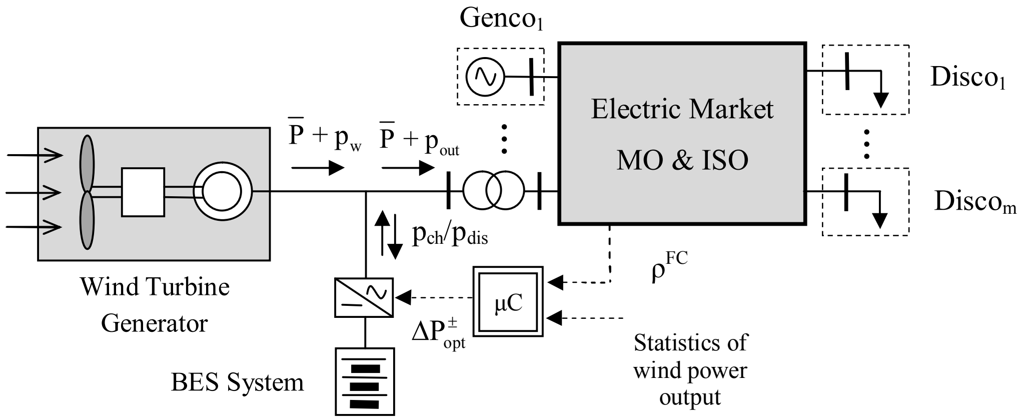

FIGURE 8.2 WIND POWER PRODUCERS IN FREQUENCY CONTROL MARKETS

where

$\overline{P}$ is the mean of wind generation,[MW]

p_w is the real-time deviation of wind generation, [MW]

p_{ch}/p_{dis} is the real-time charging/discharging of BES, [MW]

p_{out} is the output of the whole wind and battery system, [MW]

$\Delta P^{\pm}_{opt}$ is the optimal variation band, [MW]

ρ^{FC} is the price of frequency control, [$/MW]

The probabilistic model of wind power deviation (p_w) will be discussed later. The analysis in this problem is restricted to the following assumptions:

1. WPP is a price-taker in the market, *i.e.* no capable of altering the market clearing price.

2. The bidding in day-ahead spot markets is out of the scope of this problem, and without losing generality, the mean value ($\overline{P}$) is assumed to be

contracted.

3. The statistic information of the output deviation is available, *e.g.* probability density function and cumulative distribution function.

4. BMS is applied so that each battery string of BES can operate closely to the standard condition. This means the theoretical lifetime throughput can be obtained.

The problem is trade-off between the payment for frequency control and the battery cost. The cost of WPPs for a certain variation band ($\Delta P_k^{\pm}$) at stage k is:

$$C[k] = \rho_k^{FC} \cdot \Delta P_k^{\pm} + C_B[k] \tag{8.1}$$

where

k is the time index (hourly)

ρ_k^{FC} is the frequency control price at stage k, [$/MW]

$\Delta P_k^{\pm}$ is the variation band at stage k, [MW]

$C_B[k]$ is the BES cost at stage k, [$]

Assumption 4 implies that the theoretical lifetime throughput of batteries can be achieved; therefore the cost associated with 1 MWh put through the battery bank (*i.e.* charging and discharging), called battery wear cost, can be estimated as follows[39].

$$c^{bw} = \frac{C_{rep}}{NQ_{lifetime}\sqrt{\eta_{rt}}} \tag{8.2}$$

where

C_{rep} is the replacement cost of the battery bank, [$]

N is the number of batteries in the bank

$Q_{lifetime}$ is the lifetime throughput of each battery, [MWh]

η_{rt} is the roundtrip efficiency

The BES cost in stage k can be calculated as follows.

$$C_B[k] = c^{bw} \frac{1}{2}\left(\eta_{rt} \int_k p_{ch} dt + \int_k p_{dis} dt\right) \tag{8.3}$$

where

p_{ch}, p_{dis} are the charging and discharging power of BES, [MW]

In (8.3), the amount of throughput (*i.e.* charging and discharging through BES) is approximated as mean of the charging and discharging energy. This approximation is based on the fact the cumulative charging and discharging energy will converge as the time of operation. The problem then becomes determining the variation band at each hour that minimizes the total cost:

$$\min_{\Delta P_k^{\pm}} \underset{p_w(t)}{\mathrm{E}} \left\{ \rho_k^{FC} \Delta P_k^{\pm} + \frac{1}{2} c^{bw} \left(\eta_{rt} \int_k p_{ch} dt + \int_k p_{dis} dt \right) \right\} \tag{8.4}$$

8.4 SOLUTION DERIVATION

For deriving solution, it is needed to define the operation strategy of BES in this problem. That is, given a variation band, BES is used to keep the output of wind generation within this band. And to avoid the over-use of batteries (that would increase the battery cost), the strategy is that BES is only charged or discharged to make the output of WPPs laying on the boundary of the variation band when it comes out, otherwise BES does not respond, *i.e.* stand-by. The mathematical expression of the battery operation strategy is as follows.

$$p_{ch} = \begin{cases} p_w(t) - \Delta P_k^{\pm} & \text{if } \; p_w(t) \geq \Delta P_k^{\pm} \\ 0 & \text{otherwise} \end{cases} \tag{8.5}$$

and,

$$p_{dis} = \begin{cases} -\left(p_w(t) - \Delta P_k^{\pm}\right) & \text{if } \; p_w(t) \leq -\Delta P_k^{\pm} \\ 0 & \text{otherwise} \end{cases} \tag{8.6}$$

where

$p_w(t)$ is the real-time deviation of wind generation, [MW]

Take the expectation of (8.4) gives:

$$\min_{\Delta P_k^{\pm}} \overline{\rho}_k^{FC} \Delta P_k^{\pm} + c^{bw} \frac{1}{2}\left(\eta_{rt} \int_k \underset{p_w(t)}{\mathrm{E}} \{p_{ch}\} \, dt + \int_k \underset{p_w(t)}{\mathrm{E}} \{p_{dis}\} \, dt \right) \tag{8.7}$$

The "bar" on the frequency control price in (8.7) represents the expected value.

According to assumption 3, the output deviation of wind generation can be modeled as a normal (Gaussian) random variable with the probability density function as follows.

$$\mathrm{f}(p_w) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(p_w)^2}{2\sigma^2} \right) \tag{8.8}$$

where,

σ is the standard deviation, [MW]

It is further assumed that the real-time deviation has zero mean; or in other words, there is no bias in the prediction of wind power [Figure 8.3]. From (8.5) and (8.6), the energy charging to and discharging through BES can be calculated as:

$$\int_k \underset{p_w(t)}{\mathrm{E}}\{p_{ch}\}\,dt = \int_k \underset{p_w(t)}{\mathrm{E}}\{p_{dis}\}\,dt = \int_{\Delta P_k^{\pm}}^{\infty} \mathrm{f}(p_w)\left(p_w - \Delta P_k^{\pm}\right)dp_w \tag{8.9}$$

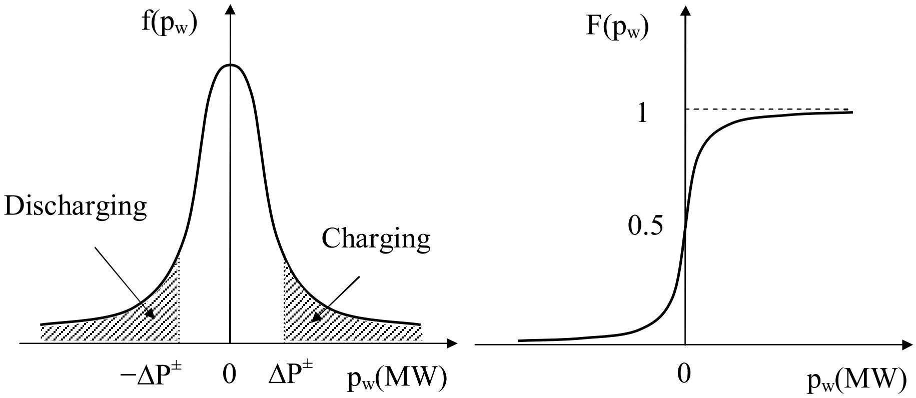

FIGURE 8.3 PROBABILITY DENSITY FUNCTION AND CUMULATIVE DISTRIBUTION FUNCTION OF POWER DEVIATIONS

Substituting (8.9) into (8.7), the problem becomes:

$$\min_{\Delta P_k^{\pm}} \overline{\rho}_k^{FC}\,\Delta P_k^{\pm} + \frac{1}{2}c^{bw}\left(1+\eta_{rt}\right)\left(\int_{\Delta P_k^{\pm}}^{\infty} \mathrm{f}(p_w)\left(p_w - P_k^{\pm}\right)dp_w\right) \tag{8.10}$$

Take derivation of (8.10) with respect to the variable band ($\Delta P^{\pm}$) and using equivalent transformation, we can obtain the optimality condition as follows.

$$\overline{\rho}_k^{FC} - \frac{1}{2}c^{bw}\left(1+\eta_{rt}\right)\left(1-\mathrm{F}\left(\Delta P_k^{\pm}\right)\right) = 0 \tag{8.11}$$

Or, when the probability density function in (8.8) is used:

$$\overline{\rho}_k^{FC} - \frac{1}{2}c^{bw}\left(1+\eta_{rt}\right)\left(1-\int_{-\infty}^{\Delta P_k^{\pm}} \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{\left(p_w\right)^2}{2\sigma^2}\right)dp_w\right)=0 \qquad (8.12)$$

where,

$F(p_w)$ is the cumulative distribution function of real-time deviation, [0, 1].

Equations (8.11) and (8.12) show the relationship between the frequency control price (ρ^{FC}), battery wear cost (c^{bw}), stochastic deviation (modeled as a Gaussian random variable) and the optimal variation band ($\Delta P^{\pm}$). Analyzing equation (8.11) and (8.12), it can be seen that the increase in ρ^{FC} will result in the decrease in $\Delta P^{\pm}$, and vice versus. Likewise, the increase in c^{bw} also results in the increase in $\Delta P^{\pm}$, and vice versus. That is true because in either cases when FC price is high or the battery wear cost is low, WPPs intend to use BES more (which, in turn, results in a smaller variation band) to avoid the expensiveness of frequency control price or take advantage of low BES cost. In contrast, when FC price is low or the battery wear cost is high, WPPs will use BES less, accompanied by a larger variation band, to take benefits from the low market price and avoid the high BES cost.

8.5 CASE STUDY

8.5.1 SYSTEM CONFIGURATION

In this section, we test the proposed scheme for battery charging/discharging in a case study. Considering a system of 10 MW wind power and 3 MWh BES used for reducing the payment for frequency control, the outline of the problem is presented in Figure 8.2. The real-time deviation of wind generation is given as Gaussian distributed model with zero mean and the standard deviation of 10 percentile of the average [Figure 8.4].

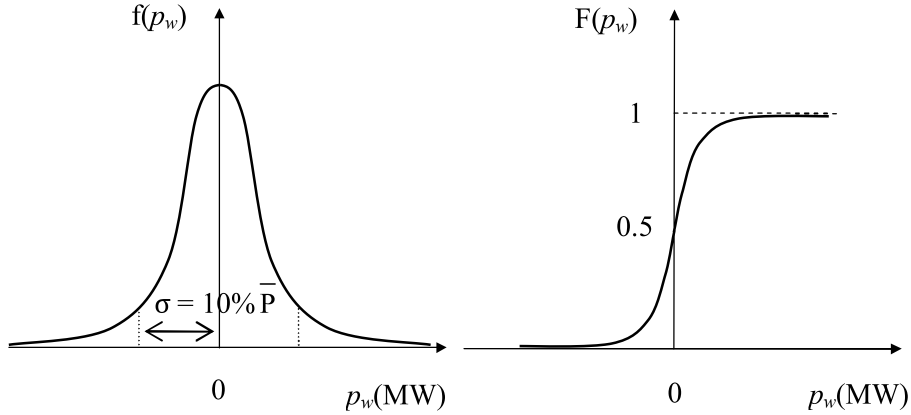

FIGURE 8.4 PROBABILITY DENSITY FUNCTION AND CUMULATIVE DISTRIBUTION FUNCTION OF POWER DEVIATIONS IN CASE STUDY

8.5.2 OPTIMAL VARIATION BANDS

BES employs the battery type 4K25SP manufactured by Surrette Battery Company. The battery wear cost is c^{bw} = \$106.5/MWh. With the prediction of frequency control price and wind generation, the optimal variation band can be obtained by the optimality condition in (8.11) or (8.12). The result is presented in Table 8.1.

TABLE 8.1 WING GENERATION, FC PRICE AND OPTIMAL VARIATION BAND

Time (hour)	$\overline{P}$ (MW)	ρ^{FC} ($/MW)	$\Delta P^{\pm}$ (MW)	Time (hour)	$\overline{P}$ (MW)	ρ^{FC} ($/MW)	$\Delta P^{\pm}$ (MW)
1	6.240	10.96	0.7505	13	6.242	16.88	0.5801
2	7.307	9.89	0.9228	14	5.058	17.34	0.4608
3	9.765	9.13	1.7729	15	6.937	16.66	0.6510
4	7.957	8.66	1.0644	16	8.167	16.14	0.7840
5	9.082	8.81	1.2064	17	5.432	18.35	0.4736
6	5.950	10.33	0.7362	18	3.835	18.98	0.3250
7	4.928	11.43	0.5803	19	3.765	17.84	0.3355
8	5.924	12.62	0.6622	20	6.242	16.07	0.6010
9	5.590	12.81	0.6196	21	9.214	16.49	0.8713
10	5.041	13.81	0.5349	22	9.794	14.80	0.9963
11	3.458	14.58	0.3548	23	9.120	12.71	1.0156
12	6.198	15.77	0.6044	24	6.024	12.05	0.6903

In order to observe the correlations of the optimal variation band ($\Delta P^{\pm}$) with the market price (ρ^{FC}) and output deviation (p_w) (which is proportional to the mean value of prediction), their normalized representation are displayed in Figure 8.5.

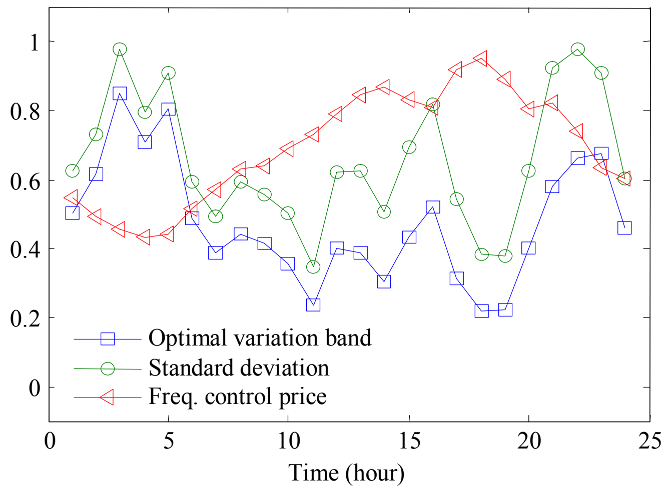

FIGURE 8.5 NORMALIZED STANDARD DEVIATION [1 MW], FREQUENCY CONTROL PRICE [$20/MW] AND THE OPTIMAL VARIATION BAND [1.5 MW]

It can be seen that the optimal variation band (square-marked) varies proportionally to the deviation of wind generation (circle-marked) and inversely to the frequency control price (triangle-marked). That is true because when the wind generation is high, meaning the real-time deviation of power outputs would be large too, WPPs should regulate BES with a large variation band to avoid the over-use of BES, *i.e.* high battery costs. This can be seen by comparing the result in 4-th and 5-th hour: the frequency control price is nearly the same but the difference in wind deviations will result in the difference in the optimal variation band. On the other hand, when the FC price is low, WPPs should take advantage of the cheap price from markets which would result in a large variation band. Comparing the result in 1-th and 13-th hour, the power deviation is close but the higher frequency control price will result in the lower optimal variation band [Figure 8.6].

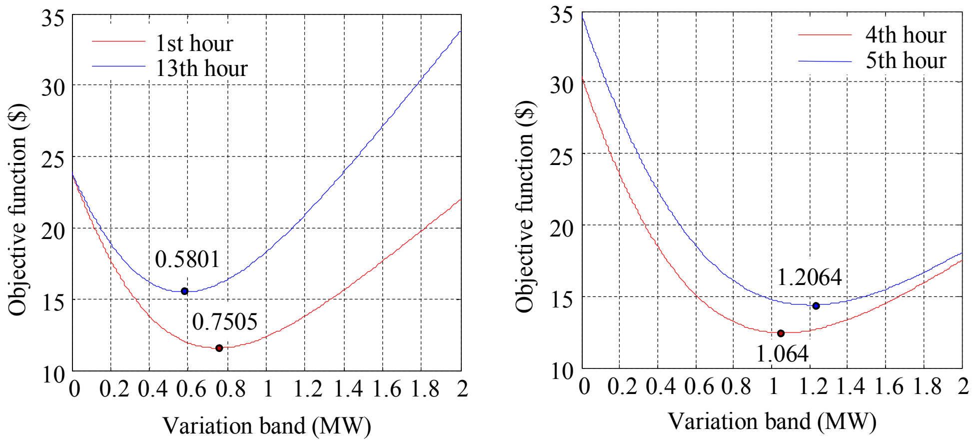

FIGURE 8.6 THE PERFORMANCE CURVE OF VARIATION BAND IN SOME STAGES

8.5.3 REAL-TIME PERFORMANCE

The real-time operation of BES in response to the optimal variation band is simulated. The real-time deviation of wind generation and the optimal variation band are presented in Figure 8.7. BES will charge or discharge if the output exceeds the pre-determined optimal band. Figure 8.7 shows the charging/discharging power of BES and the SOC during the day. It can be seen that even the cumulative energy of charging and discharging are equal, the SOC of BES gradually decreases. This is because of the loss in charging and discharging of BES. Fortunately, this problem can be handled by trading in day-ahead spot markets (but, that is out of this paper scope). It is worth noting that BES is only used when the output crosses the variation band, *i.e.* with a relatively low probability. Therefore, only a small volume of BES (3 MWh) is enough for handling the deviation of wind generation in this problem, *i.e.* keeping the synthesized output inside the optimal band [Figure 8.7].

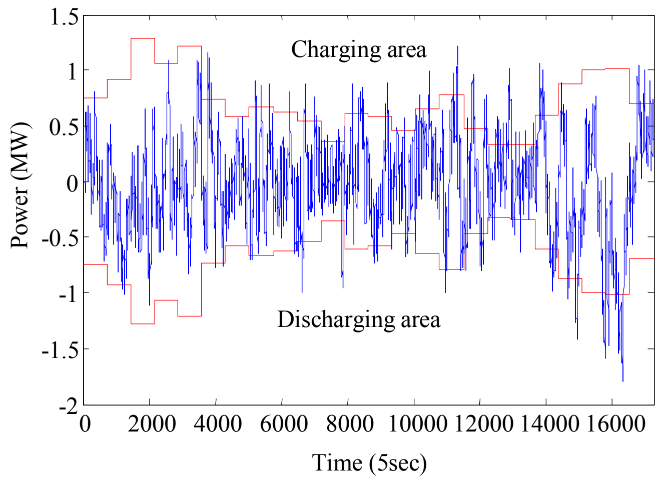

FIGURE 8.7 THE REAL-TIME DEVIATION OF WIND GENERATION AND OPTIMAL VARIATION BAND

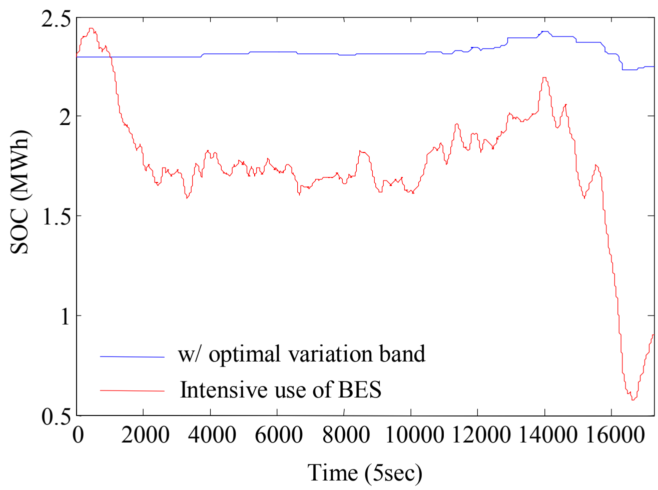

FIGURE 8.8 THE SOC WITH OPTIMAL VARIATION BAND AND INTENSIVE USE OF BATTERIES

The effectiveness of the proposed scheme compared to two other operating strategies: (1) without using BES, and (2) intensive use of BES, are illustrated. The first strategy does not use BES so that WPPs must pay for the entire variation according to the frequency control price. The second strategy, in contrast, uses BES intensively to compensate fully for the real-time variation; thus, WPPs do not need to pay any in frequency control markets. However, both strategies result in much higher costs compared to our scheme [Table 8.2].

TABLE 8.2 THE COMPARISON OF DIFFERENT OPERATION STRATEGIES

OPERATION STRATEGY	**BES COST**	**FC COST**	**TOTAL COST**
Without use of BES	$0	$341.12	$341.12
Intensive use of BES	$416.40	$0	$416.40
The proposed scheme	$33.37	$223.65	$257.02

CHAPTER IX

CONCLUSION AND FUTURE WORK

9.1 CONCLUSION

Various problems of wind power and energy storage under market environments have been resolved in this dissertation. In deregulated power systems, the electricity market is divided into several submarkets for different services: (1) markets for energy services and (2) markets for frequency control. Accordingly, the economic operation of independent Battery Energy Storage System (BESS), and then combined Battery Wind Generation Systems (BWGS) in real-time markets have been presented. In addition, we have proposed a novel scheme for BES in order to reduce the payment of wind power assuming frequency control markets. Addressing the deficiencies of the existing studies in literature, the contribution of the dissertation can be summarized into four folders as follows.

First, we have developed a new model of batteries. The model can capture the electrical properties of batteries with sufficient details, *i.e.* steady-state voltage variations, power losses and self-discharge phenomena, while is simple enough to be taken into optimization algorithms. From economic perspective, the model can evaluate the battery cost as a function of operating conditions. This is based on a lifetime model called weighted Ah-throughput.

Then, we have provided a framework for the economic operation of independent BESS in real-time markets. The problem is to control BES in response to the real-time price for maximizing profits over a day. With battery costs, the scheme would only operate BES when the discrepancy of market prices is large enough to cover its cost; otherwise, BES would rather to stay stand-by.

Considering the case of wind power under market environments, we have proposed a framework for the economic operation of combined Battery Wind Generation System (BWGS) in real-time markets. In this problem, the use of BES is not only in respond to the market price for profits, but also treating the uncertainty of wind generation, *i.e.* contracting error in the day-ahead market. The problem is compared to the case where BES and wind power operate separately and the result of higher profits in the case of combination illustrates the effectiveness of our scheme.

Finally, we have proposed a novel battery approach for wind power considering the implementation of markets for frequency control. In this problem, the use of batteries is to regulate the variation band of wind generation for minimizing both the market payment and battery cost, *i.e.* trade-off between the payment for frequency control and the battery cost. The analytic optimality condition derived in this problem shows the relationship of the optimal variation band with the frequency control price, deviation of outputs and the battery wear cost. The comparison with other strategies with respect to the payment for frequency control is also performed which shows the effectiveness of our scheme.

The analysis of this dissertation, however, is restricted to the following assumptions:

1. WPPs are price-takers who have no ability to alter the market clearing price.
2. Bidding strategy in day-ahead spot markets is out of the scope of this study; without losing generality, the mean value is assumed to be bided here.
3. An appropriate prediction tool is employed so that the prediction error and statistics of wind generation can be obtained.

4. BMS is employed to manage batteries operating closely to the standard condition. Only the impact of SOC, current and time between full charges is considered in the economic operation of BES.
5. The uncertainty of market prices (*e.g.* real-time price, frequency control price) is out of concerns; the mean of market prices is used in this study.

9.2 FUTURE WORK

The research conducted in this dissertation can be extended with various directions as follows.

The first direction is regarding the modeling of batteries. In this dissertation, the formulation of operating conditions including SOC, current and time between full charges is mainly for lead-acid batteries. This is because, amongst all types of batteries, lead-acid takes advantages of a low-cost, high efficiency and particularly, a high degree of maturity. However, battery technologies develop quickly today with lower cost while the technical performance is much improved, such as NiCa, NaS, ZEBRA and Li-ion batteries. In future work, we try to address different battery technologies with the market operation as in this dissertation.

The second direction is regarding the market price, *i.e.* real-time price, frequency control price. In this dissertation, we only consider the mean value of market prices; the uncertainty related to the price prediction is not treated properly in the optimization algorithm, *i.e.* Dynamic Programming (DP). In future work, we will try to address a comprehensive model of the market price (*i.e.* distribution function of prediction).

Finally, in this dissertation, we have discussed the idea of markets for frequency control. This market becomes very attractive and important with the tendency of power systems today: deregulation, distributed generation, renewable energy integration and distributed/decentralized control, *etc.* In such environments, the right, role and responsibility of system-users need to be clear and the frequency control market is considering the cause and effect of them with respect to a very important issue of power systems: frequency. In future work, we will explore deeper in this market idea.

BIBLIOGRAPHY

[1] J. Munksgaard, P. E. Morthorst, "Wind power in the Danish liberalised power market—policy measures, price impact and investor incentives," *Energy Policy 36*, pp. 3940-3947, Aug. 2008.

[2] P.E. Morthorst, "Wind power and the condition at a liberalized power market," *Wind Energy*, Vol.6, pp. 297-308, 2003.

[3] H. Holttinen, "Optimal electricity market for wind power," *Elsevier Energy Policy*, pp. 2052-2063, May, 2004.

[4] K. Verhaegen, L. Meeus and R. Belmans, "Development of balancing in the internal electricity market in Europe," *Proceeding of the European Wind Energy Conference*, Feb. 2006.

[5] P. Pinson, C. Chevallier and G. N. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *IEEE Transactions on Power System,* vol. 22, no. 3, August 2007.

[6] J. Matevosyan and L. Soder, "Minimization of imbalance cost trading wind power on the short-term power market," *IEEE Transactions on Power System,* vol. 21, no. 3, August 2006.

[7] G. N. Bathurst, J. Weatherill and G. Strbac, "Trading wind generation in short-term energy markets," *IEEE Transactions on Power System*, vol. 17, no. 3, August 2002.

[8] F. Bouffard and F. D. Galiana, "Stochastic security for operation planning with sgnificant wind power generation," *IEEE Transactions on Power System*, vol. 2007.

[9] A. Fabbri, T. G. S. Roman, J. R. Abbad and V. H. Mendez, “Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market,” *IEEE Transactions on Power System,* vol. 20, no. 3, August 2005.

[10] M. Marwali, H. Ma, S. Shahidehpour, K. A. Rahman, “Short-term generation scheduling in photovoltaic-utility grid with battery storage,” *IEEE Transactions on Power System,* vol. 13, Aug. 1998.

[11] B. Lu, S. Shahidehpour, “Short-term scheduling of battery in a grid-connected PV/battery system,” *IEEE Transactions on Power System,* vol. 20, May 2005.

[12] M. Korpaas, Arne T. Holen, R. Hildrum, “Operation and sizing storage for wind power plants in a market system,” *Electrical Power and Energy System 25*, pp. 599-606, 2003.

[13] G. N. Bathurst, G. Strbac, “Value of combining energy storage and wind in short-term energy and balancing markets,” *Electric Power System 67*, pp. 1-8, Jan. 2003.

[14] T. Tanabe, R. Tanikawa, I. Aoki, T. Funabashi, R. Yokoyama, “Generation scheduling for wind power generation by storage battery system and meteorological forecast,” *IEEE General Meeting*, 2008.

[15] T. Y. Lee, “Operating schedule of battery energy storage system in a time-of-use rate industrial user with wind turbine generators: A multipass iteration particle swarm optimization approach,” *IEEE Transactions on Power System,* vol. 22, Sep. 2007.

[16] R. Liang, J. Liao, “A fuzzy-optimization approach for scheduling with wind and solar energy systems,” *IEEE Transactions on Power System,* vol. 22, Nov. 2007.

[17] M. Black, G. Strbac, “Value of bulk energy storage for managing wind power fluctuation,” *IEEE Transactions on Power System*, vol. 22, March 2007.

[18] D. Yao, S. Choi, K. Yseng, T. Lie, “A statistic approach to the design of a dispatchable wind power – Battery energy storage system,” *IEEE Transactions on Power System,* vol. 24, Dec. 2009.

[19] J. G. Gonzalez, R. Muela, L. Santo and A. M. Gonzalez, “Stochastic joint optimization of wind generation and pumped-storage units in an electricity market,” *IEEE Transactions on Power System*, vol. 23, no. 2, May 2008.

[20] M. Illic, P. Skantze, C.N. Yu, L. Fink, J. Cardell, “Power exchange for frequency control (PXFC),” *IEEE Power Engineering Society 1999 Winter Meeting*, vol. 2, pp. 809-819, Feb. 1999.

[21] J. Kumar, K. Ng and G. Sheble, “AGC simulation for price-based operation – Part I: A model and Part II: Case study results,” *IEEE Transactions on Power Systems*, vol. 12, no. 2, May. 1997.

[22] B. Bakken and O. Grande, “Automatic generation control in a deregulation power system,” *IEEE Transactions on Power Systems*, vol. 13, no. 4, Nov. 1998.

[23] Prabha Kundur, *Power system stability and control,* McGraw-Hill, 1994.

[24] Thomas Ackermann, *Wind power in power systems*, John Wiley and Sons, 2005.

[25] Siegfried Heier and Rachel Waddington, *Grid integration of wind energy conversion systems*, John Wiley and Sons, 2005.

[26] Torben Skov Nielsen, Alfred Joensen, and Henrik Madsen, "A new reference for wind power forecasting", *Wind Energy,* vol. 1, pp. 29-34, 1998.

[27] Felix A. Farret and M. Godoy Simmoes, *Integration of alternative sources of energy*, IEEE press, and John Wiley and Sons, 2005.

[28] Mohammad Shahidehpour, Hatim Yamin, and Zuyi Li, *Market operation in electric power systems*, John Wiley and Sons, 2002.

[29] Choi Tae Seop, *Automated demand response system for cost saving in the smart grid environment*, Ph.D Dissertation in Seoul National University, 2012.

[30] James F. Manwell, and Jon G. McGowan, "Lead acid battery storage model for hybrid energy systems," *Solar Energy*, *vol. 50*, 1993, pp. 339-405.

[31] Per Ekdunge, "A simplified model of the lead/acid battery," *Journal of Power Sources,* vol. 46, pp. 251-262, 1993.

[32] Min Chen, Gabriel A. Rincon-Mora, "Accurate electrical battery model capable of predicting runtime and I-V performance," *IEEE Transactions on Energy Conversion*, vol. 21, pp. 504-511, 2006.

[33] K. C. Divya, J. Østergaard, "Battery energy storage technologies for power systems – An overview," *Electric Power System Research*; vol. 79, pp. 511-520, 2008.

[34] V Svoboda, H. Wenzl, H. Wenzl, R. Kaiser, A. Jossen, I. Gould, J. Manwell, P. Lundsager, H. Bindner, T. Cronin, P. Norgard, A. Ruddell, A. Perujo, K. Douglas, C. Rodriguest, A. Joyce, S. Tselepis, N. Borg, F. Nieuwenhout, N. Wilmot, F. Mattera, D. Sauer, "Operating conditions of batteries in off-grid renewable energy systems," Solar Energy, vol. 81, pp. 1409-1425, 2007.

[35] R. Kaiser, "Optimized battery energy-management system to improve storage lifetime in renewable energy systems," *Power Sources*; vol. 168, pp. 58-65, 2006.

[36] H. Wenzl, I. B. Gould, R. Kaiser, B. Y. Liaw, P. Lundsager, J. Manwell, A. Ruddell, V. Svoboda, "Lifetime prediction of batteries for selecting the technically most suitable and cost effective battery," *Power Sources*; vol. 144, pp. 373-384, 2004.

[37] J. Schiffer, D. U. Sauer, H. Bindner, T. Cronin, P. Lundsage, R. Kaiser, "Model prediction for ranking lead-acid batteries according to expected lifetime in renewable energy systems and autonomous power-supply systems," *Power Sources*; vol. 168, pp. 66-78, 2006.

[38] D. U. Sauer, H. Wenzl, "Comparison of different approaches for lifetime prediction of electrochemical systems – using lead-acid batteries as example," *Power Sources*; vol. 176, pp. 534-546, 2007.

[39] Energy modeling software for hybrid renewable energy system. HOMER Energy: Boulder, CO, USA. Available online: http://www.homerenergy.com. Developed by National Renewable Energy Laboratory, www.nrel.gov

[40] D. P. Bertsekas, *Dynamic programming and optimal control*, Athena Scientific, Belmont, Massaachusetts, 1995.

[41] Eric Allen and Marija Ilic, *Price-based commitment decisions in the electricity market,* Springer, 1999.

[42] Arthur R. Bergen and Vijay Vittal, *Power system analysis*, Prentice Hall, 2000.

[43] Gilbert M. Masters, *Renewable and efficient electric power system*, John Wiley and Sons, 2004.

[44] Minh Y Nguyen, Nack-hyun Choi and Yong Tae Yoon, "DP formulation for microgrid operation with heat and electricity constraints," *Journal of Power Electronics*, vol. 9, no. 6, 2009.

[45] Minh Y Nguyen and Yong Tae Yoon, "Battery modeling to economic operation of energy storage system in electricity markets," *International Review of Electrical Engineering*, 2013.

[46] Minh Y Nguyen, Dinh Hung Nguyen and Yong Tae Yoon, "A new battery energy storage charging/discharging scheme for wind power producers in real-time market," *Energies*, vol. 5, no. 12, 2012.

[47] Minh Y Nguyen, Dinh Hung Nguyen, and Yong Tae Yoon, "A new battery approach for wind power in frequency control market," *Journal of Electrical Engineering and Technology*, vol. 2013.

[48] Minh Y Nguyen, Van Thang Nguyen and Yong Tae Yoon, "Three-wire Network: A new distribution system approach considering both distributed generation and load requirements," *International Transactions of Electric Energy Systems*, vol. 2013.

[49] Minh Y Nguyen and Yong Tae Yoon, "A comparison of microgrid topologies considering both market operations and reliability worth," *Electric Power Components and Systems*, 2013.

[50] PJM Electric Market. Available online: www.pjm.com

[51] Denish Energy Agency. Available online: www.ens.dk

[52] Surrette Battery Company Limited. Available online: www.surrette.com

논 문 초록

최근, 화석연료 가격과 환경문제에 대한 우려의 증가는 전세계에 걸쳐 풍력설비의 폭발적 증가를 가져오고 있다. 이와 같은 추세 속에서, 풍력을 포함한 다른 신재생 에너지원은 국가적 제약(협의체의 규약- 미국: 신재생 에너지 표준, 영국: 신재생 의무, 북유럽: 차액 지원 제도) 하에 그 비중을 증가시켜오고 있다. 그러나 전력산업에 탈규제화가 이루어진 이후, 상황은 기존과 달라졌다. 신재생 에너지의 도입 역시 시장의 경쟁 방식으로 해야 한다는 주장이 대두되었다. 이러한 정책적 방향 중 하나는 일반 보조금을 지원받는 것 이외에, 풍력생산업자(WPP)가 전력시스템에 영향을 끼친다면 그것에 책임지며 그들의 생산을 위해 경쟁할 필요가 있다는 것이다. 자연자원(예: 풍속)에 의존하는 발전원이 가장 중요하게 해결해야 할 문제는 높은 수준으로 예측하는 것이다. (수요예측 오차가 평균적으로 1%~2% 이지만, 풍력 예측자원은 현재 10%~15%의 오차를 보이고 있다.) 또한, 풍력과 같은 발전원의 간헐적 특성과 기타 관련 요인(습도, 공기 밀도 등)은 풍력발전기의 출력을 불안정하고 끊임없이 변동하게 만든다. 이러한 문제는 기존의 전통적 에너지원인 원자력, 화력 및 수력발전소에 비해 풍력의 경쟁력을 낮추고 있다.

경쟁 시장환경에서 풍력 자원의 가치를 향상시키기 위해서, 많은 노력들이 소요되어왔다; 이런 노력들의 대표적 사례인 덴마크, 스웨덴, 핀란드 및 노르웨이(노드풀)등이 위치한 스칸디나비아 반도의 전력시장에 주목할 필요가 있다. 이 지역은 매우 높은 풍력자원의 비중으로 유명하며, 덴마크의 경우 2011 년 기준으로 국내 총 소비량에 20%를 차지하고 있으며, 이 반도의 많은 국가들도 풍력을 미래의 주요한 전력원으로 여기고 있다. 노드풀에서는 WPP 가 직면하고 있는 규제비용(혹은 불균형 패널티)은 전력 불균형 규제 가격의 제품으로 결정된다. 전력불균형은 앞선 계약에서 벗어난 양을 의미한다. 해당

연구 자료 및 논문을 검토하여, 우리는 풍력의 가치를 향상 시킬 수 있는 방법으로서 주요한 2 가지 방법론을 발견하였다. (1) 시장적 접근 (2) 배터리 방식.

우리의 연구는 풍력과 결합한 배터리의 에너지 저장을 제안하였으며, 이는 두 번째 연구 방법에 속한다. 연구의 방식은 배터리/풍력 전력생산 시스템(BWGS)로 논문에서 명명하였다. 본 논문의 기여는 다음의 4 가지와 같다. 첫 번째, 우리는 전기의 물리적 특성 및 경제적 특성을 충분히 고려하였지만 간단히 정리하여 배터리 문제를 최적화 문제로 모델링 하였다. 두 번째, 실시간 시장에서 독립적인 배터리 에너지 저장시스템(BESS)의 경제적 운영을 위한 프레임워크(framework)를 제공한다. 여기서 목적함수는 실시간 시장에서의 전체 매출과 배터리 비용을 포함하여, 전체 이윤을 극대화 시키는 것이다. 또한 문제는 결정론적 동적 프로그래밍(DP) 프레임워크에서 정식화되며, DP backward 방식으로 최적해 구해진다.

그 다음, 우리는 실시간 시장에서 BWGS 의 경제적 운영을 위한 프레임 워크를 제공한다. 풍력발전원의 불확실성을 고려하여, 일간 예상 이득을 최대화 하는 것은 목적함수로 설정하였다. 이 문제는 확률론적 DP 프레임워크로 정식화되며, 역시 Backward 방식으로 최적해를 구하였다. 끝으로, 주파수 제어와 관련된 시장을 고려하여, 우리는 주파수 제어 가격에 응답하는 풍력자원에 대한 배터리의 충전/발전 방식을 제안하였다. 이 문제는 주파수 제어 시장에서의 지급과 배터리 비용과의 Trade off 를 고려하여 최적 변동폭(Band)을 결정한다. 최적 상태는 해석적으로 유도되며, 최적 변동 폭과 시장가격, 출력 변동과 배터리 소모 비용 사이의 관계를 보여준다.

각 문제들은 각 사례연구에서 기존의 다른 방법과 비교하여 테스트된다. 시뮬레이션 결과는 WPP 가 시장가격의 가용성에서 매우 큰 이점이 있을 수 있다는 사실을 보여준다. 가령, 현물 가격(Spot price), 실시간가격 및 주파수 제어 가격 뿐 아니라, 예측의 오차를 추정할 수 있는 진보된 예측 방법을 보여준다. 경쟁시장 환경에서, 이러한 요소들은 시장참여자에게 기회와 도전을 줄 수 있다.

주요어:

풍력생산자, 배터리모델링, 배터리에너지저장시스템, 탈규제화, 실시간시장, 주파수제어시장, 동적프로그래밍

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